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DOCTORAL THESIS

Essays on Currency Carry Trades

Ryuta Sakemoto

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Abstract

This thesis investigates pricing models of currency carry trades. The main contribution of Chapter 2 is the use of an empirical method to summarise risk information and construct factor models. Carry trades partially share same risk characteristics with other asset markets, but some carry trade specific risk factors are also proposed. Therefore, a method to summarise overlapping information is proposed, and the type of information that is dominant in the risk factors is investigated. The important contribution of Chapter 3 is the provision of evidence of a a relationship between commodity prices and carry trade returns. Commodity prices co-move due to consumer income shocks whereas each commodity group has heterogeneity. The adopted approach takes into account these commonalities and heterogeneity. Furthermore, the overlap between commodity related information and financial market information is tested. Chapter 4 contributes with estimates of conditional factor models for carry trades. These models assume that alphas and betas are conditioned on economic states, and are time-varying. The analysis estimates alphas and betas by a nonparametric method and that allows smooth change in these parameters. Finally, the most important contribution in Chapter 5 is the investigation and provision of evidence of time variation in risk prices. Expected returns are decomposed into betas and risk prices. If expected returns change over time, then betas and/or risk prices vary over time. Recently developed dynamic factor models are adopted and used to investigate the impact of time-varying risk prices on pricing errors.

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Chapter 1

Introduction

1.1 Motivation

The foreign exchange rate (FX) market is the largest financial market compared to stock, bond and commodity markets. Daily trading volume in the FX market is three trillion U.S. dollars and the size of the trading volume is much larger than that in the stock market. For example, the daily trading volume in the New York Stock Exchange (NYSE) is 60-80 billion U.S. dollars (Bali and Yilmaz, 2015). The size of the FX market has motivated practitioner and academic study of the markets' properties, and while many advances have been made some key puzzles remain.

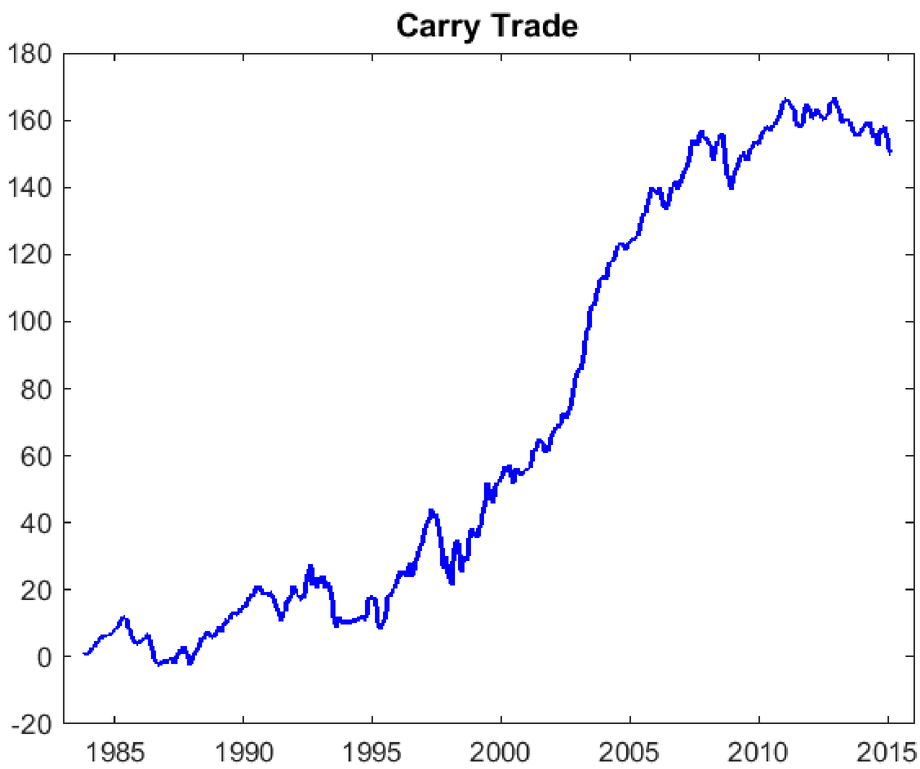
One of the most important puzzles in the FX market is the "forward discount puzzle". This puzzle is one of the main reasons for FX investors to invest in currencies of high interest rate countries. The Uncovered Interest rate Parity (UIP) condition states that a currency in a high interest rate country should depreciate against a currency in a low interest rate country. In other words, the interest differential should be offset by the change in the spot exchange rate. Bilson (1981), Fama (1984), and many empirical studies document violations of the UIP. The forward discount puzzle not only matters for investors, but also for international economics, since many models assume that the UIP relation is satisfied.

Early studies have mainly focused on a single currency and investigated the time-series relation between an interest rate differential and an exchange rate (e.g. Backus et al. 1993; Bekaert and Hodrick, 1993). This approach had the drawback that it was sensitive to a currency specific component. Recently, a portfolio approach was introduced by Lustig and Verdelhan (2007), following a similar approach adopted by research in stock markets (e.g. Fama and French, 1992). The portfolio approach focused on a cross-sectional relation across currencies and sorted them based upon one characteristic. This procedure allowed the construction of currency portfolios and each containing currencies of similar characteristics. For instance, Lustig and Verdelhan (2007) sorted currencies based upon interest rate differentials and constructed high and low interest rate currency portfolios. The portfolio approach was desirable because the currency specific component was averaged out, which allows for investigation of the relation between currency returns and currency characteristics. The currency characteristics were not only interest rate differentials. For instance, Menkhoff et al. (2012b) employed past currency excess returns, and Sarno and Schmeling (2014) used GDP growth to construct currency portfolios.

The currency portfolio approach generated empirical evidence that investing in currencies in high interest rate countries yields a higher average return, suggesting that high interest rate currencies are more risky than low interest rate currencies. Figure 1.1 displays the cumulative return of a carry trade portfolio computed as the return difference between high and low interest rate currency portfolios. This is calculated based upon monthly data. The average return is positive but there is a large negative return around the financial crises of 1997 and 2008.

Many articles document the positive carry returns, regardless of portfolio

FIGURE 1.1: Cumulative return of the carry trade portfolio



Notes:This figure provides the cumulative return of the carry trade portfolio. Six currency portfolios are constructed based upon forward discounts. The carry return is computed as the return spread between low and high interest rate currency portfolios.

construction methods. For instance, Lustig and Verdelhan (2007) used interest rates and spot exchange rates to compute portfolio returns. Currencies were sorted based upon the interest rate differentials from the U.S., and assigned into eight portfolios at an annual frequency. Christiansen et al. (2011) focused on daily data and calculated carry returns as the interest rate differentials minus changes in the spot exchange rates. Lustig et al. (2011) and Menkhoff et al. (2012a) adopted spot and forward exchange rates, and computed forward discounts, since the forward discounts were approximately equal to the interest differentials under the Covered Interest rate Parity (CIP) condition as reported by Akram et al. (2008). Forward discount data were advantageous in terms of data availability. The currencies were then sorted based upon the forward discounts and the portfolios were rebalanced at a monthly frequency. Monthly returns were widely used in the literature since many finance and macro data were available at a monthly frequency (e.g. Bakshi and Panayotov, 2013; Dobrynskaya, 2014; Lettau et al., 2014; Atanasov and Nitschka, 2015).

The main interest of the previous literature in carry trades is to search for risk factors that explain the positive carry returns. If investing in high interest rate currencies is risky, the positive carry returns would be reward for taking risk. To identify risk factors, two aspects are investigated in this thesis. First, the co-movements between the risk factors and the portfolio returns are investigated. These co-movements are captured by the factor betas (factor exposures). High beta indicates that the portfolio return is more sensitive to changes in the risk factors. The component that the risk factors cannot explain is the alpha. It is unsystematic risk and is generated by a currency specific reason. Alpha is also considered as profitability for investors because it is not related to the factor exposure, and may therefore reflect other aspects such as fund manager's skill. In carry trade studies, two factor models are often employed. For instance, Lustig et al. (2011) use the dollar as the first factor. The dollar factor shows the average return for U.S. investors who invest in foreign currencies, and it has a similar function as the market factor in stock market research. Lustig et al. (2011) also introduce the carry factor (high minus low interest rate currency portfolios, HML_{FX}) as the second factor. Menkhoff et al. (2012a) adopt the dollar and the FX market volatility innovation factors. Lustig et al. (2011) and Menkhoff et al. (2012a) report that their models explain time series fluctuations of portfolio returns, and alphas are not statistically significant. Christiansen et al. (2011) introduce a regime switching model to estimate factor betas. The betas depend upon the states that are governed by FX market volatility. They find that the factor exposure to the stock market risk is higher during the high volatility regime.

Second, this thesis tests whether risk factors are priced (i.e., whether their risk premiums are significant). The expected return is decomposed into the factor betas and the risk prices. If the risk factors can account for carry returns, the risk prices should be obtained. Note that all currency portfolios have the same risk prices while each portfolio has different betas, therefore each portfolio has a different expected return. Lustig et al. (2011) report that the carry factor has a positive risk price, and Menkhoff et al. (2012a) show that the risk price of the FX volatility factor is negative. The downside stock market also contains risk that is priced in carry portfolios, as reported by Atanasov and Nitschka (2014), Dobrynskaya (2014) and Lettau et al. (2014).

1.2 Structure

A range of risk factors have been used to explain carry returns in currency portfolios. These factors include: the return spread between high and low interest rate currency portfolios (Lustig et al., 2011), innovations in FX market volatility (Menkhoff et al., 2012a; Ahmed and Valente, 2015), FX market skewness (Rafferty, 2011), market liquidity (Brunnermeier et al., 2009), stock market return (Lettau et al., 2014), downside stock market return (e.g. Dobrynskaya, 2014), and durable and nondurable consumption growth (Lustig and Verdelhan, 2007). There may be considerable overlap in these factors since risks flow from one market to another, e.g. from stock to FX markets. Chapter 2 therefore provides a method to summarise these risk factors better.

In chapter 3, a test is conducted on whether commodity prices contain risk that is priced in currency carry portfolios. Commodity prices in a country are related to the inflation rate of that country. It means that commodity prices are important components in the determination of interest rates, which are key in carry returns. Production of commodities depends upon natural resource conditions, and hence it may explain heterogeneity of interest rates across countries.[1] Recently, Ready et al. (2016) propose a direct theoretical link between currency carry trades and commodity prices. Commodity exporting countries are more robust to consumption shocks since these countries can produce input goods domestically. It suggests that their saving rates are low due to the weak demand of precautionary saving, and therefore interest rates are high relative to those of commodity importing countries. This difference in the economic structure between commodity importing and exporting countries produces interest differentials and carry returns.

In chapter 4, the importance of time-varying alphas and betas on carry trade factor models is tested. To this end, conditional factor models are adopted. Alphas and betas are conditioned on state variables and are time-dependent. This chapter tests whether alphas and betas vary over time and investigates the main drivers of this time variation. This is a reasonable assumption since there

[1]The relation between commodity prices and currencies has been investigated by Chen and Rogoff (2003) and Chen et al. (2010). They found commodity exporting countries' currencies contain information for future commodity prices.

is empirical evidence that violations of UIP depend upon economic states, which would provide a rational for positive carry returns. For instance, Bansal (1997), and Bansal and Dahlquist (2000) show that UIP does not hold only when the interest rate in the U.S. is higher than the interest rate in a foreign country.

The analysis in chapter 5 focuses on the time variation in risk prices as well as that of betas. To this end, a time-varying risk price model is employed. Time-varying risk prices represent time variation in investors' risk aversion. This is plausible since currency carry trades have crash risk, and investors change their degree of risk aversion before and after a financial crisis. The analysis provides estimates of time-varying risk prices and investigates the main drives of this time variation.

1.3 Research Questions

This thesis pauses a number of research questions related to the empirical modelling of FX carry returns in currency portfolios. For example in Chapter 2 the question asked is: How can the information in a range of risk factors be best summarised? Is principle components analysis (PCA) reasonable? How does an empirical model perform with respect to explaining the variation in the data, while risk price parameters and betas are significantly and correctly signed, with small pricing errors? How much co-movement exists between the various risk factors?

The relevance to carry trades of commodity price information is investigated in Chapter 3. The following questions are considered: What types of commodities are related to carry returns? Does information about aggregate commodity prices explain carry returns? What currencies are more sensitive to commodity price information? Do commodity prices contain information that is different from that provided by stock and bond markets?

Time-varying profitability of carry trades are explored in Chapter 4 and the following questions considered: Are there significant alphas in carry trade factor models? Do alphas and betas change over time? If they do, what are the main drivers of these changes? Do all betas co-move? What kind of liquidity information is more related to the time variation?

Finally, time-varying risk prices for carry trades are investigated in Chapter 5 where the following questions are considered: Are time-varying risk prices more important than time-varying betas in generating smaller pricing errors? What drives time variation in the risk prices? What is the difference between market liquidity and FX market volatility in the carry trade risk prices? Does the approach followed in this thesis show a better fit compared with a normal rolling regression approach? How do up-side and down-side market states impact on risk prices?

1.4 Contribution

The analyses presented in this thesis makes a number of contributions. This thesis has many contributions to the carry trade and asset pricing literature. Chapter 2 contributes by suggesting an empirical method for summarising risk information. Investors do not depend upon small amount of data for their investment decisions, rather they decide based on rich information. Econometricians do not usually observe the extent of the data set that investors use, hence a common factor is a reasonable proxy for the investor information set. Chapter 2 adopts a common factor approach to examine overlapped information between carry trade and equity market risks. This approach is also suitable for currency carry portfolios in terms of estimation. The number of currency portfolios is relatively smaller than that of equity portfolios, hence there is an inherent problem of degrees of freedom. The approach circumvents this problem by focusing only on the common information.

Moreover, Chapter 2 identifies the most relevant information for the common factor. This is important since if high explanatory power of the common factor depends upon specific information, we should use that information directly. Another motivation of our approach is that each data is assumed to be noisy and entails measurement errors, and the common factor approach can help in this regard.

The most important contribution in Chapter 3 is that the testing of whether commodity price information is related to carry returns. The commodity price factors considered in this thesis take into account commodity price commonalities. Commodity prices co-move due to income shocks for consumers (Alquist and Coibion, 2014). The recent empirical literature also presents other rational for commodity price commonalities (e.g. Byrne et al. 2013; Gospodinov and Ng, 2013; West and Wang, 2014). However, there are several types of commodities and it is reasonable to assume that some shocks impact on certain types of commodities more than on others. Ignoring the commonalities within certain commodity types and extracting only common factors across all commodities, would cause weak common factors or idiosyncratic errors (Moench et al., 2013). To avoid this problem, Chapter 3 adopts the dynamic hierarchical factor model (DHFM) proposed by Moench et al. (2013). This model allows for both, the extraction of common factors across data and those within certain types of data.

The other contribution in Chapter 3 is a times-series investigation of the carry factor. The carry factor is calculated as the return spread between high and low interest rate currency portfolios and explains cross-sectional returns of carry portfolios (Lustig et al. 2011). However, the type of information contained or captured by this factor is still in contention. To this end, information content is investigated in a time series context.

The first contribution in Chapter 4 is the investigation of conditional factor models for currency carry portfolios. Conditional factor models assume that alphas and factor betas vary based upon changes in economic states. The difficulty of estimation is that econometricians do not know the true specification between the state variables and the betas. Lewellen and Nagel (2006) circumvent this problem by using high frequency data because such data ought to better reflect fluctuations in economic states. This chapter follows Lewellen and Nagel (2006) and uses daily data to extract rich information. Furthermore, this chapter adopts the nonparametric approach proposed by Ang and Kristensen (2012). This approach allows for more reflective changes in alphas and betas, and for testing whether alphas and betas vary over time.

The second contribution in Chapter 4 is the investigation of the drivers of time variation in alphas and betas. Baillie and Kim (2015) test the capacity of some macro fundamentals in explaining time variation in deviations from UIP. However, their study focuses on single currencies, and hence the currency specific component may affect their results. This chapter uses currency portfolios instead, and therefore the relationships between betas and macro fundamentals are robust.

The main contribution of the analysis in Chapter 5 is the investigation of time variation of risk prices as well as factor betas. Time variation of risk prices lead to better fitting factor models in stock and bond market research (Ferson and Harvey, 1991; Adrian et al., 2015). Since currency carry trades share common characteristics with other asset markets, time-varying risk prices may also play a substantial role for carry trades.[2]

Finally, the analysis is extended to investigate the drivers of time variation in risk prices. This is carried out with a particular focus on the drivers of the dollar and carry factors, being the two predominant factors for carry trades. Since these factors are obtained by a data driven approach, interpretation is required. We follow Adrian et al (2015) and estimate time-varying risk prices. This estimation method provides interpretation of the time variation in risk prices.

1.5 Results

The empirical results in Chapter 2 show that the PCA approach is successful in extracting common information across risk factors. The common factor model prices currency carry portfolios. This model shows a better fit than other factor models in terms of pricing errors and R^2. This thesis reports that FX volatility and stock market returns contain information that is important for the common factor, whereas the correlation of these variables is moderate.

The analysis in Chapter 3 finds that agricultural material and metal prices contain information relevant to carry returns. However, common information across all types of commodities is not successful in pricing carry portfolios. This is investigated further and the analysis reports that currencies in emerging countries are linked to the agricultural material factor, while those in developed countries are related to the metal factor. The carry factor contains commodity and financial market information and they do not overlap.

In Chapter 4, empirical evidence is presented that both alphas and betas

[2] For example, both carry trade and stock market models have exposures to downside stock market risk.

change over time. The average time-varying alphas are statistically significant, which implies that two factors are not sufficient to explain carry portfolio returns. Further analysis shows that fluctuations of alphas are related to the business cycle and the high (low) interest rate currency portfolio has a lower (higher) alpha during recessions. The U.S. short-term interest rate and the TED spared are the main drivers of the change in the betas of the dollar factor. Moreover, the term spread, the bid-ask spread and the Corwin and Schultz (2012) liquidity measure affect fluctuations in the beta of the FX volatility factor.

In Chapter 5, the empirical evidence is presented that time-varying risk prices lead to smaller pricing errors in factor models. Market liquidity plays a main role in the time variation of the dollar factor, and FX market volatility is most important for the carry factor. Both the time-varying beta and risk price model and the constant beta and time-varying risk price model provide a better fit than rolling regression models. The average positive risk price on the carry factor is supportive of the evidence that the risk price is higher in up markets than in down markets.

1.6 Methodology

In this section, relevant econometrics methods for this thesis are briefly summarised. First, the Fama and MacBeth (1973) approach is described, and this method is used to obtain the risk price on a risk factor. It is a two-step approach where the return of each portfolio is regressed on a risk factor to obtain an estimate of the beta on that factor. At this step the sensitivity of portfolio returns to a risk factor is investigated. Since expected returns are calculated as the product of the risk price and the betas, the second step involves regressing the factor betas on the expected returns to obtain an estimate of the risk price. However, this method has a problem because the estimation errors in the first step may affect the statistical inference in the second step. To deal with the problem, Shanken (1992) proposes a correction to the standard errors that takes into account estimation errors. Cochrane (2005) and Burnside (2011) use the Generalized Method of Moment (GMM) instead to adjust for estimation errors. This thesis employs Shanken's approach while the GMM approach is also reported in the Appendix. Using the estimated betas and risk prices, the predicted returns are obtained. This thesis adopts the procedure of calculating pricing errors by the differences between realized and predicted returns, and to investigate model fitting (see Figures 3.1 and 5.3).

Second, this thesis uses the principal component analysis (PCA) approach that is widely used to summarise information. This approach is powerful in extracting common information from a large number of data. Investors do not depend upon narrow information, rather they make their investment decisions based on a large amount of data. For instance, Ludvigson and Ng (2007, 2009) use the PCA approach to predict stock and bond returns. In particular, this approach is suitable for macroeconomic data since such data is aggregated and contains measurement errors. Extracting common components across data series mitigates the effects of each data's measurement errors.

Further, the analysis in Chapter 3 uses the dynamic hierarchical factor model (DHFM). The basic idea comes from the PCA, but the DHFM approach allows the extraction of common information within data subsets. This is beneficial for interpretation, because one of the problems of the PCA is that it is difficult to interpret the estimation results. Moreover, the DHFM has a hierarchical relation between the overall dataset and subsets of it. In the context of this thesis, it is reasonable to assume that commodity price information is partially linked to overall macroeconomic data.

Time-varying models are employed in Chapters 4 and 5. A kernel-weighted least squares approach is adopted. This approach exploits local information as rolling window regressions. The advantages of kernel-weighted regressions is that it allows for smooth change in the coefficients. A rolling regression approach provides rapid change in coefficients and causes over-estimation, as pointed out by Ghysels (1998). Kernel-weighted regressions mitigate this problem. Moreover, the window size is determined by data in the kernel-weighted approach, while rolling regressions do not have any criteria for a suitable window size.

Chapter 2

Common Information in Carry Trade Risk Factors

2.1 Introduction

The carry trade is an investment strategy that involves borrowing in a low interest rate currency and investing in a high interest rate currency. Applying this strategy to many currencies allows for the building of currency portfolios and the diversification of some market risk, as proposed by Lustig and Verdelhan (2007). They focus on cross-sectional interest rate differentials and show that a high interest rate currency portfolio yields a higher average return than a low interest rate currency portfolio. In seeking to extend Lustig and Verdelhan (2007), several risk factors have been proposed in the carry trade literature. These can be generically categorized into currency and non-currency factors. Currency factors exploit readily available foreign exchange market information. For example, Lustig et al. (2011) propose the return difference between high and low interest rate currency portfolios, and Menkhoff et al. (2012a) suggest innovations of global foreign exchange volatility as currency factors. Non-currency factors exploit macro or finance information. For instance, Lustig and Verdelhan (2007) use U.S. durable and nondurable consumption growth, based on the Consumption-Capital Asset Pricing Model (C-CAPM). Atanasov and Nitschca (2014), Dobrynskaya (2014), and Lettau et al. (2014) investigate downside stock market risk for the FX market. Although most studies explore either currency or non-currency risk factors, these factors may be related to each other, since many institutional investors invest across assets. This chapter proposes to test the incremental benefit of combining the information embedded in both currency and non-currency factors previously identified in the literature.

It can be argued that common risk information is important from both a theoretical and an empirical perspective. Lustig et al. (2011) propose a no-arbitrage model which has common and country-specific factors. Heterogeneity across currencies in the exposure to the common factor is substantial, and is relevant for positive carry trade returns. In their model, the country specific factors are averaged out in each portfolio, therefore the common factor plays an important role. From an empirical perspective, common risk factors have been identified when modelling excess returns in the bond market (see Ludvigson and Ng, 2009). The common information across exchange rates are explored by Engel et al. (2015). They find that the common factor extracted from exchange rates themselves includes information that is not extracted from macroeconomic fundamentals. Giglio et al. (2016) construct an index to capture the common component in some systemic risk measures. They present empirical evidence that the common index can predict macroeconomic shocks more accurately than a large cross-section of risk measures can do individually. The carry factor (high minus low interest rate currency portfolios HML_{FX}) proposed by Lustig et al. (2011) prices cross-sectional carry returns. However, this factor uses information from only two portfolios of currencies. If a common factor is important for carry trades, this factor may be enhanced by adding information embedded in the other factors.

This chapter contributes in the following ways. First, this chapter is able to identify common information in currency and non-currency risk factors for carry trades. This allows us to test whether adding non-currency information to currency information help us to better price carry portfolios. This is important since Lettau et al. (2014) find that stock market risk is common between currency carry trades and other assets. The proposed approach allows to consider financial and macro risk more generally, since it examines the overlap between currency and non-currency risk, and the latter includes stock market risk. In terms of the second contribution, the approach reduces dimensionality in a large cross-section of risk factors. Although the FX portfolio approach averages out the impact of outliers, the number of currency portfolios used in the literature reduces the degrees of freedom, and hence the ability to consider several factors simultaneously. The proposed approach avoids this difficulty by using a single common factor. Finally, the empirical approach is to be recommended since it is free from potential multicollinearity problems. One risk factor may be correlated with others, and hence multicollinearity may affect the estimation results. The approach allows to extract the common factor even when the number of risk factors increases.

The empirical results show that the extracted common factor can price currency portfolios in both time series and cross-sectional contexts. In the cross-section, relevant tests fail to reject the null hypothesis that there is no pricing error. In addition, the model exhibits a high R^2 and low root mean squared error. This chapter also considers the incremental usefulness of the common factor using an orthogonalization that identifies the factor's marginal information. Evidence is presented that the common factor has additional explanatory power compared with global FX volatility innovations and downside world stock market risk. This common factor is strongly related to the high interest rate currency portfolio. These results are also robust to transaction costs.

The rest of this chapter is organized as follows: Section 2.2 reviews the related carry trade literature, Section 2.3 describes the methodology and the dataset, Section 2.4 presents a discussion of the empirical results, Section 2.5 sets the robustness tests of key results, and Section 2.6 concludes.

2.2 Brief Literature Review

Positive returns of currency carry trades are dependent upon systematic deviations from Uncovered Interest rate Parity (UIP) condition. UIP suggests a high interest rate country's currency depreciates against a low interest rate country's currency. This parity condition has been called into question by empirical evidence (see Fama, 1984; Lewis, 1995; and Engel, 1996). Most studies focus on bilateral currency relations, while Lustig and Verdelhan (2007) use a portfolio approach to sort currencies based on cross-sectional interest rate differences. The portfolio approach exploits diversification benefits and generates a higher Sharpe ratio than those of individual currencies or the U.S. stock market (see Burnside et al., 2011). Das et al. (2013) indicate that carry trades have different characteristics from international stocks, U.S. bonds, real estates, and commodities. The carry trade portfolio is used by Das et al. (2013) as the new asset class to enhance the entire portfolio performance.

High profitability of currency carry trades depends upon market states, such as market volatility, and liquidity. The most widely used state variable is FX market volatility. For instance, Christiansen et al. (2011) adopt a smooth transition regression model with factor betas are governed by FX volatility. They show that carry trades have high exposure to the stock market when FX volatility is high. Copeland and Lu (2016) find that most profits of carry trades are attributed to low FX volatility periods. They propose an enhanced trading strategy which adopts carry during low FX volatility periods and real exchange rate deviation during high FX volatility periods. Using the component GARCH model, Ahmed and Valente (2015) decompose Menkhoff et al.'s (2012a) global FX volatility into short-run and long-run components and show that the long-run component has a risk premium. They find this long-run component related to U.S. macro fundamentals. Dos Santos et al. (2016) also focus on short-run and long-run components and investigate their risk premium for each emerging currency. They model the residuals of the UIP regression by the component GARCH-M model. They present evidence that the short-run component is related to speculative pressures, whereas the long-run component is associated with macro fundamentals. Market liquidity is also important for carry trades. It is argued by Brunnermeier et al. (2009) that carry trades have crash risk when speculators are subjected to funding constraints. They use the TED spread to measure funding constraints, and show that it predicts future returns of carry trades. Orlov (2016) compares liquidity in the stock market with that in the exchange rate market and shows that the latter is the dominant factor in determining carry returns. Although these studies highlight the pricing relevance to the cross-section of currency portfolios of specific types of information, the common component across these types has not been properly examined.

2.3 Methodology and Data

2.3.1 Estimation Procedure

To identify the risk price of a common factor for carry returns, this chapter uses the Fama and MacBeth (1973) two-step approach. First, the excess carry return, $r_{j,t}$, of currency portfolio j at time t, can be explained by a risk factor h_t. The first stage Fama-MacBeth time series regression is used to determine the beta (β_j) associated with this factor for each portfolio:

$$r_{j,t} = \alpha_j + \beta_j h_t + e_{j,t}. \tag{2.1}$$

Central to this analysis, the risk price, λ, is obtained by a second cross-sectional regression of the portfolios' time series average excess returns $E[r_j]$ on the estimated betas $\hat{\beta}_j$:

$$E[r_j] = \lambda \hat{\beta}_j + er_j \tag{2.2}$$

where er_j is a cross-sectional error term. Since these betas are estimated values, estimation uncertainty should be taken into account in statistical inference. Accordingly, this study employs the Shanken (1992) standard errors to account for estimation uncertainty. Burnside (2011) also adopts the Shanken approach. These standard errors add an adjustment for the effect of the variance-covariance matrix of the factor.

The common information across currency and non-currency factors is extracted by principal components. Define $\mathbf{X}$ to be the $T \times N$ standardized risk factors matrix with elements, $x_{i,t}$, $i = 1, \ldots, N$, $t = 1, \ldots, T$. This study uses nine risk factors and hence $N = 9$. Each risk factor, $x_{i,t}$, is decomposed into a common factor, f_t, and an idiosyncratic component, $\epsilon_{i,t}$, as:

$$x_{i,t} = \Lambda_i f_t + \epsilon_{i,t} \tag{2.3}$$

where Λ_i is the loading on the common factor.

This study constructs a factor mimicking portfolio, F_t. The factor mimicking portfolio allows us to represent the factor information as a traded asset. This also helps in comparisons of the explanatory power of factors, especially that some of the factors that this chapter considers (explained below) are traded assets while others are not. This is carried out to take account of Menkhoff et al.'s (2012a) observation that the difference between traded and non-traded assets may affect empirical results of the performance of portfolio strategies. Accordingly, the factor mimicking portfolio is used. This is obtained by the following two steps. First, a common factor f_t is regressed onto six carry trade portfolio returns $\mathbf{R_t}$:

$$f_t = a + b'\mathbf{R_t} + \eta_t \tag{2.4}$$

where the parameter a is a constant and η_t is the error term. Next, using the estimated b and the return vector, as $\hat{F}_t = \hat{b}'\mathbf{R_t}$, the factor mimicking portfolio $\hat{F}_t$ is obtained. The risk factor h_t in equation (2.1) is replaced by the mimicking portfolio $\hat{F}_t$.

2.3.2 Carry Risk Factors

This section now sets out nine carry trade risk factors prominently used in the recent literature. The first four risk factors are currency based and are denoted with subscripts FX, while the other five factors are non-currency based. This study also utilises the dollar (DOL) factor, which is standard in the literature, and this study typically includes it in all specifications.[1]

1. $HML_{FX,t}$ is the high minus low currency portfolio return mentioned in Lustig et al. (2011). It is the return spread between the highest interest rate portfolio (P6) and the lowest interest rate portfolio (P1).

2. $\Delta VOL_{FX,t}$ is the global FX volatility innovations. This study uses the following two steps as in Meknhoff et al. (2012a) to calculate this variable. Let the daily log return of currency j on day τ be $r_{j,\tau} = s_{j,\tau} - s_{j,\tau-1}$, where $s_{j,\tau}$ is the log of the spot exchange rate on day τ. First, global FX volatility, $\sigma_{FX,t}$, in month t is estimated as:

$$\sigma_{FX,t} = \frac{1}{T_t}\sum_{\tau=1}^{T_t}\sum_{j=1}^{K_\tau}\left(\frac{|r_{j,\tau}|}{K_\tau}\right) \tag{2.5}$$

[1] DOL is computed as the average of all currency excess returns.

where $|r_{j,\tau}|$ is the absolute value of $r_{j,\tau}$, K_τ is the number of currencies on day τ, and T_t is the total number of trading days in month t. Then volatility innovations are estimated as the residuals of a AR(1) process for $\sigma_{FX,t}$.

3. $SKEW_{FX,t}$ is the global FX skewness proposed by Rafferty (2011). First, month t skewness of currency j, $SKEW_{j,t}$ is calculated.

$$SKEW_{j,t} = \frac{1/T_t \sum_{\tau=1}^{T_t}(r_{j,\tau} - \bar{r}_j)^3}{\left[1/T_t \sum_{\tau=1}^{T_t}(r_{j,\tau} - \bar{r}_j)^2\right]^{3/2}} \tag{2.6}$$

where $\bar{r}_j$ is the sample average of $r_{j,\tau}$ within month t. Since negative skewness is bad (good) for investing (funding) in a currency, the sign of the skewness is adjusted based on the forward discount of currency j at the end of month $t-1$, $fw_{j,t-1} - s_{j,t-1}$, where $fw_{j,t-1}$ ($s_{j,t-1}$) is the log of the forward (spot) exchange rate of currency j. The global FX skewness is calculated by:

$$SKEW_{FX,t} = \frac{1}{K_t}\sum_{j=1}^{K_t} sign(fw_{j,t-1} - s_{j,t-1})SKEW_{j,t}. \tag{2.7}$$

This study also uses the innovation part of $SKEW_{FX,t}$, but this has no qualitative effect on the results, as shown in the robustness section.

4. $\Delta LVOL_{FX,t}$ is the long-run global FX volatility innovations.[2] Ahmed and Valente (2015) estimate long-run volatility from the global FX market using the component GARCH model proposed in Engel and Lee (1999). The conditional variance of average daily currency return $\bar{r}_\tau$ is decomposed into short-run and long-run components as:

$$\bar{r}_\tau = \psi_1 + u_\tau,\ u_\tau = \sigma_\tau \eta_\tau,\ \eta_\tau \sim i.i.d.N(0,1) \tag{2.8}$$

$$\sigma_\tau^2 - q_\tau = \psi_2(u_{\tau-1}^2 - q_{\tau-1}) + \psi_3(u_{\tau-1}^2 - q_{\tau-1})d_{\tau-1} + \psi_4(\sigma_{\tau-1}^2 - q_{\tau-1}) \tag{2.9}$$

$$q_\tau = \psi_5 + \psi_6(q_{\tau-1} - \psi_5) + \psi_7(u_{\tau-1}^2 - \sigma_{\tau-1}^2) \tag{2.10}$$

[2] Ahmed and Valente (2015) report that the long-run component is important pricing currency carry portfolios. Including the short-run part does not affect the common factor. See the Appendix.

where $\sigma_\tau^2 - q_\tau$ is the short-run component and q_τ is the long-run component of the conditional volatility σ_τ. Daily series are used for estimation and picked up the end of month values to construct the monthly series (see Ahmed and Valente, 2015). The first difference of the monthly series are taken to extract innovations.

5. ΔTED_t is the TED spread innovations. The TED spread is the difference between the three month Eurodollar LIBOR rate and the three month Treasury bill rate.[3] This value reflects banks' funding constrains. Brunnermeier et al. (2009) show that the TED spread helps to predict future carry trade returns. This study extracts the innovation component as the first difference.

6. $Wmkt_t$ is the global stock market excess return which this study approximates by the MSCI world index return (U.S. dollar base). The one month Treasury Bill rate is used as the risk free rate and is subtracted from the world index return.

7. $DWmkt_t$ denotes the downside global stock market excess return which is computed using a dummy variable, that is equal to 1 if the world stock market excess return is negative, and zero otherwise.[4] This study slightly changes the definition of Dobrynskaya (2014) to highlight downside information as follows:[5]

$$DWmkt_t = dummy \times Wmkt_t. \tag{2.11}$$

8. and 9. ΔNC_t and ΔC_t are nondurable and durable consumption growth. Monthly growth rates in real per capita nondurables and durables

[3]Instead of the three month LIBOR, this study uses the three month interbank rate in the U.S. to cover a longer period.

[4]Downside risk has also been considered by Farhi and Gabaix (2016).

[5]Dobrynskaya (2014) uses the upside market dummy and it does not allow us to extract downside market information as a single variable.

consumption are used, which is adopted by Kan et al. (2013). This study employs personal durable and nondurable consumption expenditure data and adjust them using the consumer price index (durable and nondurable goods) and total population.[6]

This study first presents premia facia evidence that these risk factors are correlated using Pearson correlation coefficients (See the Appendix). This supports the major contention that there is common information in the carry trade factors and spill-overs between currency and non-currency risks.

This study uses 48 currencies over the period November 1983 through December 2013. The currencies are the same as those analyzed by Menkhoff et al. (2012a). As is standard in this literature, six portfolios are constructed based on the forward discount at monthly frequency. The U.S. dollar is taken as the base currency, since this study takes the perspective of an U.S. investor. Following Lustig et al. (2011), trading costs are taken into account in portfolio construction by using bid and ask prices when buying and selling currencies. Further, the data is pre-treated using the method of Darvas (2009) who adopts the previous day's observations when there is no difference between bid and ask prices, or the spread of the forward rates is smaller than that of the spot rates.

2.4 Empirical Results

2.4.1 Asset Pricing Model

The main contribution of this chapter's approach is the enhanced modelling of both the time series and cross-sectional characteristics of carry trade

[6]Consumption CAPM justifies utilising the risk associated with durable and nondurable consumption growth, for further details see Lustig and Verdelhan (2007).

TABLE 2.1: Asset Pricing Model

Panel A: Factor Betas

Portfolio	α	DOL	F		adj-R^2
P1	0.05	1.28***	-2.21***		0.93
	(0.04)	(0.02)	(0.10)		
P2	-0.09	1.12***	-1.12***		0.88
	(0.05)	(0.03)	(0.13)		
P3	0.03	1.06***	-0.50***		0.90
	(0.05)	(0.03)	(0.13)		
P4	0.02	0.83***	0.91***		0.88
	(0.05)	(0.03)	(0.15)		
P5	-0.06	0.97***	0.45***		0.85
	(0.05)	(0.04)	(0.15)		
P6	0.04	0.73***	2.46***		0.89
	(0.05)	(0.04)	(0.17)		

Panel B: Risk Prices

Risk Factor	(1)	(2)	(3)	(4)	(5)
DOL	0.18	0.18	0.18	0.18	0.18
	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)
F	0.12***				
	(0.03)				
HML_{FX}		0.49***			
		(0.12)			
ΔVOL_{FX}			-0.08***		
			(0.02)		
$Wmkt$				0.40***	
				(0.12)	
$DWmkt$					0.22***
					(0.06)
R^2	0.88	0.87	0.78	0.87	0.88
RMSE	0.05	0.06	0.08	0.06	0.06
χ^2	7.16	8.74*	10.89**	8.75*	7.58
[p-value]	[0.13]	[0.07]	[0.03]	[0.07]	[0.11]

Notes: This table displays asset pricing results from the Fama and MacBeth (1973) two pass procedure. Test assets are six all country currency portfolios. Panel A: Factor Betas provides time series regressions of excess returns of carry trade portfolios on a constant (α), and the common factor (F) using equation (2.1). The standard errors are reported in parentheses and obtained by the Newey and West (1987) procedure with optimal lag selection according to Andrews (1991). The adjusted R^2 is also reported. Panel B: Risk Prices presents cross-sectional pricing results of the linear factor model. The coefficient of factor risk premium λ is estimated using equation (2.2). A constant term is excluded in the cross-sectional model. HML_{FX} is the high minus low currency portfolios, ΔVOL_{FX} is the global FX volatility innovations, $Wmkt$ is the world stock market excess return and $DWmkt$ is the downside world stock market excess return. Shanken (1992) standard errors are reported in parentheses (·). The R^2 is a measure of fit between the sample mean of excess return and the predicted mean return. The RMSE is the root of mean-squared error and is reported in percentage points. The χ^2 test statistics of pricing errors are reported and the null hypothesis is that there is no pricing error. p-values are reported in square brackets[·]. Asterisk *,**, and *** indicate significance at the 10%, 5% and 1% level, respectively. The sample period is from November 1983 to December 2013.

portfolios. This study controls for the dollar risk (DOL) in all regressions since this has been found to be important in capturing time series fluctuations of carry returns. First, this study focuses on Panel A in Table 2.1, which provides estimates of factor betas by the time series regressions of equation (2.1). All factor betas on the common factor F are statistically significant at the 1% level. They increase approximately monotonically from P1 to P6. This suggests that low interest rate currency portfolios act as a hedge against carry risk. None of the constant terms α are statistically significant, which implies that DOL and F successfully capture the time series fluctuations of currency portfolios. These results support the argument that the common factor models the time series behaviour of carry returns. This study now considers the relative performance of time series standard risk factors. With reported insignificant betas or significant alphas, alternative risk factors prominent in the literature do not account for the time series behaviour of currency returns as successfully as the common factor, and this statement is evidenced in the Appendix.

Panel B of Table 2.1 reports the cross-sectional asset pricing results. This is also important in assessing the performance of the common risk factor for carry returns. This study runs the cross-sectional regression using equation (2.2) but a constant term is not included as proposed by Burnside (2011), since the constant term may affect the risk price estimation result. The results tabulated in Panel B column (1) shows that the risk price on the common factor is statistically significant at the 1% level. A R^2 of 88% indicates a very good model performance. Moreover, the results show that there is no significant pricing error for the empirical factor, since this study is unable to reject the null hypothesis of pricing errors with the χ^2 test in Table 2.1. For comparison purposes columns (2) to (5) present estimation results using other prominent factors in the carry trade literature. In these columns, HML_{FX} and FX market volatility innovations are currency factors, and the 'world stock market' and ‘downside stock market’ are non-currency factors. All four are computed by using mimicking-portfolios. The cross-sectional model in column (1) is at least as good as any of the others in terms of a statistically significant risk price, a high R^2, and the pricing error test, whilst also having the smallest RMSE.

2.4.2 Comparison with Other Risk Factors

Having identified the usefulness of the common factor for carry returns, this section next formally tests whether the common factor can price cross-sectional carry trade portfolio returns better than the other factors individually. This section focuses on HML_{FX} and innovations in the global FX volatility as currency factors, and the downside world stock market excess return as a non-currency factor. The result of the stock market return is not reported since it is similar to that of the downside stock market return.[7] Following Menkhoff et al. (2012a), this study uses an orthogonalization to avoid factor correlation and to identify which factor provides additional information. If the orthogonalized factor with respect to a comparative is statistically significant, this implies that there is incremental information not contained in the comparative factor.

Table 2.2 column (1) restates the results that the common factor is important for carry returns. This contrasts with columns (2), (3) and (4) which indicate that the other orthogonalized factors are not statistically significant when included with the common factor. These orthogonal risks are denoted by superscript “Orth” for HML_{FX}, ΔVOL_{FX}, and $DWmkt$. Hence, the remaining information in the standard factors does not contribute substantially to explaining carry returns. The common information in currency and non-currency factors is enough to explain the carry, and remaining risks elsewhere are less

[7]See the Appendix.

TABLE 2.2: Cross-sectional Returns and Orthogonalized Common Factor

Risk Factor	(1)	(2)	(3)	(4)
DOL	0.18	0.18	0.18	0.18
	(0.12)	(0.12)	(0.12)	(0.12)
F	0.12***	0.12***	0.12***	0.12***
	(0.03)	(0.03)	(0.03)	(0.03)
HML_{FX}^{Orth}		0.07		
		(0.07)		
ΔVOL_{FX}^{Orth}			0.02	
			(0.06)	
$DWmkt^{Orth}$				-0.01
				(0.02)
R^2	0.88	0.89	0.94	0.90
RMSE	0.05	0.05	0.04	0.05
χ^2	7.16	7.16*	4.94	6.66*
[p-value]	[0.13]	[0.07]	[0.18]	[0.08]
Risk Factor	(5)	(6)	(7)	
DOL	0.18	0.18	0.18	
	(0.12)	(0.12)	(0.12)	
HML_{FX}	0.48***			
	(0.12)			
ΔVOL_{FX}		-0.08***		
		(0.02)		
$DWmkt$			0.20***	
			(0.05)	
F^{Orth}	0.02	0.02*	0.03**	
	(0.02)	(0.01)	(0.01)	
R^2	0.89	0.94	0.90	
RMSE	0.05	0.04	0.05	
χ^2	7.16*	4.94	6.68*	
[p-value]	[0.07]	[0.18]	[0.08]	

Notes: This table presents comparison results between the common factor F and other factors. $Orth$ indicates the factor is orthogonalized with respect to the comparative factor. These cross-section regression results are estimated by equation (2.1). HML_{FX} is the high minus low currency portfolios, ΔVOL_{FX} is the global FX volatility innovations, and $DWmkt$ is the downside world stock market excess return. Shanken (1992) standard error are reported in parentheses $(\cdot)$. The R^2 is a measure of fit between the sample mean of excess return and the predicted mean return. The RMSE is the root of mean-squared error and is reported in percentage points.The χ^2 test statistics of pricing errors are reported and the null hypothesis is that there is no pricing error. p-values are reported in square brackets $[\cdot]$. Asterisk *,**, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

relevant. Columns (5), (6), and (7) of Table 2.2 show the results of the orthogonalized common factors. This study investigates whether the remaining information in the common factor price cross-sectional currency portfolios. While column (5) does not indicate which factor dominates, taken together with the RMSE and pricing error results in Table 2.1, this study can conclude that the common factor is superior to HML_{FX}. Another advantage of the approach is that the common factor exploits more diversified information. In contrast, HML_{FX} extracts information only from the high and low interest rate currency portfolios, and, as will be discussed in the next section, this is more sensitive to the choice of currencies. Table 2.2 columns (6) and (7) show that the orthogonalized common factors F^{Orth} are statistically significant, which indicates that the common factor contains information not captured by ΔVOL_{FX} and $DWmkt$ on their own. This is particularly clear in column (7) since F^{Orth} is statistically significant at the 5% level. The implication is that downside stock market information is insufficient in explaining currency carry returns and risks important for the carry trade are more prevalent than those that originate in the stock market.

2.4.3 Developed Country Sample

Currencies of some emerging countries may be less liquid than those of developed countries, and this may affect the results, see also Lustig et al. (2011). This is investigated by considering a subsample of 15 developed countries to represent "liquid" currencies. The 15 currencies are the same as those included in the dataset of Lustig et al. (2011). Table 2.3 presents the time series and cross-sectional results for these countries. From Panel A, four of the five betas on the common factor are statistically significant, and increase monotonically from P1 to P5. Panel B presents the cross-sectional results. Although the R^2 is not

TABLE 2.3: Asset Pricing in Developed Countries

Panel A: Factor Betas

Portfolio	α	DOL	F		adj-R^2
P1	0.12***	1.31***	-2.96***		0.94
	(0.04)	(0.02)	(0.10)		
P2	-0.14**	1.07***	-0.67**		0.83
	(0.06)	(0.04)	(0.15)		
P3	-0.06	1.01***	0.04		0.89
	(0.05)	(0.02)	(0.15)		
P4	-0.01	0.78***	1.50***		0.87
	(0.05)	(0.03)	(0.12)		
P5	0.09**	0.83***	2.09***		0.94
	(0.05)	(0.02)	(0.12)		

Panel B: Risk Prices

Risk Factors	(1)	(2)	(3)	(4)	(5)
DOL	0.19	0.19	0.19	0.19	0.19
	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)
F	0.09***				
	(0.03)				
HML_{FX}		0.33**			
		(0.14)			
ΔVOL_{FX}			-0.06***		
			(0.02)		
$Wmkt$				0.31***	
				(0.11)	
$DWmkt$					0.16***
					(0.06)
R^2	0.60	0.53	0.59	0.76	0.68
RMSE	0.09	0.10	0.10	0.07	0.09
χ^2	8.23**	9.82**	9.03**	5.03	6.40*
[p-value]	[0.04]	[0.02]	[0.03]	[0.17]	[0.09]

Notes: This table displays asset pricing results from the Fama and MacBeth (1973) two pass procedure. Test assets are five developed country currency portfolios. Panel A: Factor Betas provides time series regressions of excess returns of carry trade portfolios on a constant (α), and the common factor (F) using equation (2.1). The standard errors are reported in parentheses and obtained by the Newey and West (1987) procedure with optimal lag selection according to Andrews (1991). The adjusted R^2 is also reported. Panel B: Risk Prices presents cross-sectional pricing results of the linear factor model. The coefficient of factor risk premium λ is estimated using equation (2.2). A constant term is excluded in the cross-sectional model. HML_{FX} is the high minus low currency portfolios, ΔVOL_{FX} is the global FX volatility innovations, $Wmkt$ is the world stock market excess return and $DWmkt$ is the downside world stock market excess return. Shanken (1992) standard errors are reported in parentheses $(\cdot)$. The R^2 is a measure of fit between the sample mean of excess return and the predicted mean return. The RMSE is the root of mean-squared error and is reported in percentage points. The χ^2 test statistics of pricing errors are reported and the null hypothesis is that there is no pricing error. p-values are reported in square brackets $[\cdot]$. Asterisk *,**, and *** indicate significance at the 10%, 5% and 1% levels, respectively. The sample period is from November 1983 to December 2013.

the best across the five models, the risk price on the common factor is statistically significant at the 1% level. In contrast, HML_{FX}, which is the second best model in Table 2.2, is statistically significant at only the 5% level, and the R^2 is the smallest. This result implies that the common factor contains diversified information and, hence, it is more robust to against a sample of currencies.

TABLE 2.4: Marginal R^2 of All Risk Factors

Risk Factor	All countries	Developed countries
HML_{FX}	0.20	0.24
ΔVOL_{FX}	0.55	0.54
$SKEW_{FX}$	0.03	0.04
$\Delta LVOL_{FX}$	0.48	0.50
ΔTED	0.17	0.18
$Wmkt$	0.56	0.57
$DWmkt$	0.60	0.62
ΔC	0.00	0.01
ΔNC	0.00	0.01

Notes: The table shows the R^2 from regressing individual data series onto the common factor, following Ludvigson and Ng (2009). HML_{FX} is the high minus low currency portfolio return, ΔVOL_{FX} is the global FX volatility innovations, $SKEW_{FX}$ is the global FX skewness, $\Delta LVOL_{FX}$ is the long-run global FX volatility innovations, ΔTED is the TED spread innovations, $Wmkt$ is the global stock market excess return, $DWmkt$ is the downside global stock market excess return, ΔC is the durable consumption growth, and ΔNC is the nondurable consumption growth.

2.4.4 Interpretation of the Factor

Earlier empirical results show that the proposed approach does well in extracting information relevant to the asset pricing model. Although the common factor is related to all risk factors, it is unlikely that the link is the same for every factor. This section, therefore, examines the relationship to each separate risk factor. Following Ludvigson and Ng (2009) in modelling bond markets, the marginal R^2 is calculated by regressing each risk factor on the common factor. Table 2.4 presents the results of the Marginal R^2. This study observes the FX market volatility and the stock market are strongly related to the common factors, since their marginal R^2 is greater than 0.5. In contrast, HML_{FX}, which is computed from currency portfolio returns, is less strongly linked to the common factor compared with volatility and the stock market. Although both F and HML_{FX} have a good fit in Table 2.1, they provide different information. These results also show that the common factor does not load on to a specific factor and the information it carries is diversified across risk factors. In addition, these results are similar between all and developed countries. This evidence supports the earlier discussion that the proposed approach is more robust to the choice of the countries. It is also interesting to note that the marginal R^2 of the consumption factors are almost zero. This is mostly due to the idea that monthly consumption data is very noisy, as pointed out by Brandt et al. (2006).

TABLE 2.5: Beta Sorted Portfolios

Panel A: All countries							
	P1	P2	P3	P4	P5	P6	P6-P1
mean	0.63	1.65	2.41	3.11	2.76	6.17**	5.54***
	[0.48]	[1.00]	[1.34]	[1.64]	[1.40]	[2.50]	[2.63]
std.dev	6.01	7.52	8.99	9.43	9.76	10.74	9.95
Panel B: Developed countries							
	P1	P2	P3	P4	P5		P5-P1
mean	-0.29	1.02	1.78	3.18	5.55***		5.84***
	[0.17]	[0.52]	[0.80]	[1.60]	[2.58]		[2.90]
std.dev	9.01	9.75	10.40	9.95	10.83		10.10

Notes: This table reports annualized mean and annualized standard deviations for currency portfolios sorted by currency betas to the common factor. The betas are computed by a rolling time-series regression of individual currencies' excess returns on the common factor. The moving window size is 36 months. Newey and West (1987) HAC t-statistics are reported in squared brackets [$\cdot$]. Asterisks *,**, and *** indicate significance at the 10%, 5% and 1% levels, respectively. The sample period is December 1986 to December 2013. There are only five portfolios for developed countries subsample, since there is a smaller number of currencies.

2.4.5 Beta Sorted Portfolios

If the common factor is a risk factor for currencies, currencies would have systematic factor exposure differences to this factor's risk. Hence, the beta sorted portfolios will also generate return differences across currency portfolios. To this end, this section sorts portfolios based on betas to a risk factor, instead of the forward discount. This is the approach adopted in Lustig et al. (2011) and Menkhoff et al. (2012a). To sort by betas this study first estimates a factor beta by regressing each currency excess return on a constant and the common factor. A sample window of 36 months is used. After obtaining the currency factor beta in month $t-1$, this study sorts the currencies based on the factor betas and computes the currency excess return of portfolios in month t. Table 2.5 presents the results of portfolios sorted by the common factor betas. For the full sample of countries and for the subsample of developed countries, returns increase approximately monotonically from the first to the last portfolios. High exposure portfolios, which are P6 for all countries and P5 for developed countries, have statistically significant positive returns. More importantly, the return differences between the last and the first portfolios are statistically significant at the 1% level. This implies that the common factor bears systematic risk to currencies.

2.5 Robustness

The results in the previous section show that the common factor prices currency portfolios. This section examines the robustness of the empirical results. This study has used the two factor model in the previous section, as is standard in the literature. Nevertheless, the dollar factor (DOL) may be correlated to the world stock market return, since U.S. dollar based stock market returns have exposure to the base currency. Table 2.6 shows the results of the asset pricing model using a constant term, instead of the average U.S. dollar factor. This change does not affect the results. Time series betas on the common factor and cross-sectional risk prices are statistically significant at the 1% level.

TABLE 2.6: Asset Pricing Model: One Factor Model

All countries				Developed countries			
Panel A: Factor Betas							
	α	F	adj-R^2		α	F	adj-R^2
P1	-0.07	0.85***	0.03	P1	0.10	-0.01	0.00
	(0.14)	(0.31)			(0.16)	(0.34)	
P2	-0.19	1.58***	0.12	P2	-0.15	1.73***	0.11
	(0.14)	(0.30)			(0.15)	(0.29)	
P3	-0.07	2.05***	0.20	P3	-0.08	2.30***	0.22
	(0.12)	(0.28)			(0.14)	(0.31)	
P4	-0.06	2.91***	0.43	P4	-0.02	3.25***	0.45
	(0.10)	(0.27)			(0.10)	(0.22)	
P5	-0.16	2.79***	0.33	P5	0.08	3.96***	0.54
	(0.11)	(0.26)			(0.12)	(0.22)	
P6	-0.02	4.23***	0.65				
	(0.09)	(0.18)					
Panel B: Risk Prices							
	const	F	RMSE		const	F	RMSE
λ	-0.15	0.14***	0.05	λ	0.00	0.09***	0.09
	(0.15)	(0.03)			(0.16)	(0.03)	
R^2	0.89			R^2	0.60		
χ^2	7.16			χ^2	8.37**		
[p-value]	[0.13]			[p-value]	[0.04]		

Notes: This table displays asset pricing results from the Fama and MacBeth (1973) two pass procedure. Panel A: Factor Betas provides time series regressions of excess returns of carry trade portfolios on a constant (α), and the common factor (F) using equation (2.1). The standard errors are reported in parentheses and obtained by the Newey and West (1987) procedure with optimal lag selection according to Andrews (1991). The adjusted R^2 are also reported. Panel B: Risk Prices presents cross-sectional pricing results of the linear factor model. The coefficient of factor risk premium λ is estimated using equation (2.2). A constant term is employed, instead of the dollar risk (DOL). Shanken (1992) standard errors are reported in parentheses $(\cdot)$. The R^2 is a measure of fit between the sample mean of excess return and the predicted mean return. The RMSE is the root of mean-squared error and is reported in percentage points. The χ^2 test statistics of pricing errors are reported and the null hypothesis is that there is no pricing error. p-values are reported in square brackets $[\cdot]$. Asterisk *,**, and *** indicate significance at the 10%, 5% and 1% level, respectively. The sample period is from November 1983 to December 2013.

The adjusted R^2s imply that the common factor is strongly associated with the high interest rate currency portfolios. This is consistent with the beta sorted portfolio results in Table 2.5. The impact of risk prices is almost similar to the model that has DOL.

Further six robustness results are included in the Appendix. This study will describe six tests and show that all robustness test results support the common factor. The first robustness test that this study considers here relates to the procedure of constructing the mimicking portfolio. This study tests whether altering this procedure affects the estimation results. The common factor f is used rather than using the mimicking portfolio. Panel A in Table A.5 provides empirical evidence that this change does not affect the results. In the second test, this study increases the number of test portfolios to examine whether the small number was driving the results. Lewellen et al. (2010) propose to include portfolios sorted by other characteristics in the stock market context, when test portfolios have a factor structure. Following Menkhoff et al. (2012b), momentum portfolios are constructed based on the past one month currency excess returns. For all countries, six momentum portfolios are constructed, and for developed countries, five momentum portfolios are used. Panel B in Table A.5 shows that once the momentum portfolios are included, the common factor remains statistically significant at the 1% level.

Third, this study adopts a country-level asset pricing model. Lustig et al. (2011) and Ahmed and Valente (2015) argue that the country-level model can deal with the data-snooping biases mentioned by Lo and MacKinlay (1990), and the information problems presented by Ang et al. (2010).[8] The data snooping bias is more serious when a portfolio approach is used. Further, the portfolio approach may lose substantial information, as shown by Ang et al. (2010). To deal with these possible drawbacks of the portfolio approach, it may be useful to use individual currencies instead. Panel C in Table A.5 shows that the R^2 becomes smaller than that of the portfolio approach, but the factor is still statistically significant at the 1% level and the magnitude is similar to the portfolio result. Fourth, this study adds a global bid-ask spread innovation factor. This factor is used in Menkhoff et al. (2012a) who show that it can price the cross-sectional currency portfolios. Since the common factor is related to the change in the TED spread, as reported in the Appendix, other liquidity measures may enhance the explanatory power. Panel D reports the results, and it shows that the effect of including the bid-ask spread innovation factor is marginal. The fifth robustness test contains the short-run global FX volatility innovation factor. Although Ahmed and Valente (2015) show that the long-run volatility component is substantial for the carry trade asset pricing model, the short-run volatility component may affect the result. However, Panel E shows that the impact of the short-run volatility is small. Finally, this study includes the change in global FX skewness. As most factors proposed in the previous literature focus on innovation parts, the innovation component of the global FX skewness is employed. The results in Panel F suggest that this factor also does not play an important role.

[8] Lo and MacKinlay (1990) present evidence that finding a portfolio construction idea and testing it on the same dataset, leads to a data snooping bias. Ang et al. (2010) provide evidence that a risk premium depends upon the cross-sectional distribution of beta and idiosyncratic volatility. If this study uses portfolios, some information of the beta distribution are lost.

2.6 Conclusion

The literature presents evidence of a number of risk factors that can explain carry trade returns. But are these currency and non-currency risks complements or substitutes? In particular, are all carry risks sourced from the stock market, or do they originate elsewhere? This chapter investigates these questions by seeking to summarise a range of risk factor information to model currency carry trades. This chapter tests whether common information extracted from currency and non-currency risk factors previously explored in the literature better capture risk information to price the time series and the cross-section of currency returns. The motivation is based upon theoretical and empirical findings in the literature. For example, Lustig et al. (2011) present a theoretical model and show heterogeneous exposure to the world common risk is a main driver for positive currency carry returns. There is empirical evidence in other assets that the common factor approach successfully extracts substantial information (e.g., Ludvigson and Ng, 2009; Engel 2015 et al., 2015; Giglio et al., 2016). The high minus low interest rate currency portfolios factor, HML_{FX}, can price the cross-sectional carry returns well, as shown by Lustig et al. (2011). However, this factor uses information extracted from only two portfolios and, hence, the common factor approach may present a better alternative to HML_{FX}.

This chapter finds a common factor exists that summarises currency and non-currency information reasonably well. Although downside stock market risk is widely used in the currency carry trade literature, such as by Atanasov and Nitschca (2014), Dobrynskaya (2014), and Lettau et al. (2014), the empirical results suggest that there are risk characteristics of carry portfolios that are not captured by the downside stock market risk. This result implies the currency and stock markets are not completely integrated. In addition, the common factor does not depend upon a specific risk factor. The proposed approach appears to be more robust against a change in the sample compared to the HML_{FX} factor. Therefore, it is advantageous to use a much broader range of information when modelling carry trade risks.

Chapter 3

Carry Trades and Commodity Risk Factors

3.1 Introduction

The carry trade is an investment strategy that involves borrowing in a low interest rate currency and investing in a high interest rate currency. Many studies present evidence that the carry trade yields positive excess returns, and linear risk-based models may explain these returns.[1] This rapidly expanding literature and in the previous chapter has identified several important factors in carry trade pricing. This chapter extends the literature by building an empirical factor model in a data rich environment, with a particular focus upon the role of commodity prices.

Previous studies report that financial market or macro information, may be fruitful in modelling carry trade risk factors. In terms of financial market information, Menkhoff et al. (2012a) find that global Foreign Exchange (FX) volatility innovations are negatively correlated with high interest rate currency portfolios. Other FX market information in the form of average U.S. dollar returns

[1] Lustig and Verdelhan (2007) were the first to apply a risk-based model on the returns of currency carry trade portfolios. Other prominent papers in this field include Burnside (2011, 2012), Lustig and Verdelhan (2011), Lustig et al. (2011), Menkhoff et al. (2012a), and Atanasov and Nitschka (2015).

(DOL) and the return difference between high and low currency portfolios (HML_{FX}) have also been found important (see Lustig et al., 2011). Further, Atanasov and Nitschka (2014), Dobrynskaya (2014), and Lettau et al. (2014) show that equity market downside risk can price carry returns better than the conventional capital asset pricing model (CAPM).

In addition to financial market information, macro fundamentals, such as measures of consumption and production activity, may also be related to currency carry trades. Lustig and Verdelhan (2007) show that excess returns of high interest rate currency portfolios are correlated with U.S. durables and nondurables consumption growth. Ang and Chen (2013), Burnside (2012), Jordà and Taylor (2012), and Sarno and Schmeling (2014) examine whether macroeconomic information is related to currency carry trades, but are more cautious in drawing the conclusion that macro variables can be successfully identified as risk factors in currency carry trades.

Commodity prices however are a possible source of macro-finance information that may be useful for carry returns and, as yet, have not been formally considered in the cross-sectional carry trade literature. Chen and Rogoff (2003) and Chen et al. (2010) present time series evidence that the currencies of commodity producing countries, such as Australia and Canada, are linked to commodity prices over time.[2] Also in a time series context, Bakshi and Panayotov (2013) show that the change in a commodity price index can predict excess returns of carry trades at quarterly frequency. Passari (2015) proposes the construction of currency portfolios based on currency returns as predicted by commodity prices. The high minus low commodity strategy factor in this context, however, does not price cross-sectional portfolios. In a recent theoretical

[2]Chen et al. (2010) show that exchange rates can predict a commodity price index at quarterly frequency.

contribution, Ready et al. (2016) propose a model in which a commodity importing country has more consumption risk compared to a commodity exporting country. They indicate that the interest rate in the commodity importing country is lower than that of the commodity exporting country due to precautionary savings. They also test their model and identify that commodity exports are related to carry returns.

The analysis in this chapter contributes to the literature on carry trade returns on three fronts. First, this chapter extends the work of Bakshi and Panayotov (2013), Passari (2015), and Ready et al. (2016) by utilising commodity prices as a risk factor for carry trade portfolios. This chapter explores the cross-sectional relation between carry trade returns and commodity prices. In particular, this chapter investigates whether commodity common information can price cross-sectional currency portfolios. Given that the recent literature finds that commodity prices exhibit commonality (e.g., Byrne et al., 2013; Gospodinov and Ng, 2013; Alquist and Coibion, 2014; and West and Wang, 2014), this chapter focuses on a commodity common factor. However, different types of commodities may contain different information.[3] The proposed approach examines common factors across commodity sectors and within particular commodity sectors. This is the most significant difference from Passari (2015) and Ready et al. (2016) who also investigate cross-sectional currency portfolios and risk factors. Passari (2015) uses commodity price indices and Ready et al. (2016) employ an import ratio factor computed as the aggregate net exports of basic goods and net imports of finished goods relative to a country's output. Importantly, the commodity factor is not based on trade data, which is published with lags, but on more readily available commodity prices, and accounts for both commonalities between, and heterogeneity across, different

[3] Yin and Han (2015) report that commodity price movements have heterogeneity across types of commodity. Chen et al. (2014) show that the combination of commodity prices has much more information than the aggregate commodity index.

types of commodity. Moreover, this chapter constructs portfolios at a monthly frequency in contrast to Passari (2015) and Ready et al. (2016). Also, this chapter's portfolios take into account trading costs while Ready et al. (2016) do not due to their low frequency portfolio construction.

This chapter's second contribution is to exploit an empirical factor model to summarise a wide range of information, including the macro-finance data highlighted in the prior literature on carry trade returns. Ludvigson and Ng (2007, 2009), Engel et al. (2015) and Filipou and Taylor (2015) use empirical factor models in time series forecast studies of stock markets, bond yields and exchange rates. When modelling a small number of cross-sectional portfolios, as with carry trades, the ability to effectively summarise a large array of risk factors becomes important. To this end, this chapter employs the Dynamic Hierarchical Factor Model (DHFM) proposed by Moench et al. (2013). This model has a hierarchical structure that specifies common and block factors, which is useful in accounting for commodity heterogeneity. A further advantage is that empirical factors are more readily identifiable.

The chapter's third contribution is that the proposed approach to modelling commodities provides interpretation of the carry factor (high minus low interest rate currency portfolio, HML_{FX}). The HML_{FX} can capture the cross-sectional return differences of currency portfolios and is related to global market risk (see Lustig et al., 2011). Menkhoff et al. (2012a) further report that HML_{FX} is also associated with FX market volatility. The exact content of HML_{FX}, however, is still unclear, as pointed out by Burnside (2012), possibly because it is constructed from the carry portfolios themselves. Accordingly, this chapter examines, in a time series context, whether the commodity prices factors have additional information that accounts for HML_{FX}.

The empirical results provide evidence that commodity price factors can price currency carry trades, and that there is heterogeneity across the types of commodity. This chapter finds that the agricultural material and metal factors are associated with the cross-section of currency excess returns. The agricultural material factor is especially linked to emerging currency portfolios, and the metal factor is related to developed currency portfolios. This chapter also finds the stock market risk is not linked to emerging currency portfolios. These findings are important, since the previous literature has not focused on the heterogeneity between developed and emerging currency portfolios. The related studies consider a world common factor, and developed and emerging currency portfolios have exposure to the same risk. This common factor is considered to be related to financial market risk (e.g., Lustig et al., 2011; Atanasov and Nitschka, 2014 and Dobrynskaya, 2014). The finding suggests that there is risk that is somewhat segmented from financial markets but related to commodity prices. This commodity price risk is tied to emerging market currencies. The empirical results are supported by the findings of Bodart et al. (2012) and Habib and Stracca (2012). Bodart et al. (2012) focus on emerging countries that depend upon the export of a single commodity good and show a positive relationship between commodity prices and emerging countries' exchange rates. Habib and Stracca (2012) demonstrate that a reversal of carry trades during the financial crisis has a clear pattern only in developed currencies.

The remainder of this chapter is organized as follows: Section 3.2 presents the method of constructing carry trade portfolios, Section 3.3 lays out the econometric framework and presents the empirical factor model, Section 3.4 discusses the empirical results, Section 3.5 presents further analysis, and Section 3.6 concludes.

3.2 Currency Portfolios

This chapter starts by defining the currency excess return and describing the construction of carry trade portfolios. Let s_t be the log of the spot exchange rate at time t in foreign currency per unit of domestic currency, and f_t be the log of the forward exchange rate at time t to be delivered at time $t+1$. A rise in s_t is a domestic currency appreciation, and the domestic currency is assumed to be the U.S. dollar (USD). Following Lustig et al. (2011), the currency carry return is computed as:[4]

$$r_{t+1} = f_t - s_{t+1}. \tag{3.1}$$

This strategy is implemented by selling the dollar forward, f_t, in the current period and buying the dollar spot, s_{t+1}, in the next period. This study sorts currencies into six portfolios, P1 to P6, based on their forward discounts, $f_t - s_t$. P1 contains the lowest interest rate currencies and P6 contains the highest interest rate currencies. These are rebalanced at the end of each month. The log excess return of a portfolio is calculated as the equally-weighted average of the log excess returns of the currencies in that portfolio.

As in Lustig et al. (2011), this study uses bid and ask quotes to account for transaction costs. A carry return pricing factor that is not robust to transaction costs is less appealing to investors. When an investor buys the foreign currency, she sells the dollar forward at the bid price, f_t^b, at time t and buys the dollar at the ask price, s_{t+1}^a, at time $t+1$. The excess return of going long in the foreign currency is:

$$r_{t+1}^l = f_t^b - s_{t+1}^a. \tag{3.2}$$

[4]This return is related to violation of the Uncovered Interest rate Parity (UIP). See the Appendix.

Conversely, when the investor sells the foreign currency, the excess return of going short is:

$$r^s_{t+1} = -f^a_t + s^b_{t+1}. \tag{3.3}$$

Following previous studies, portfolio P1 is considered as the short position with excess return, r^s_{t+1}, and the other portfolios are considered as long positions with excess returns, r^l_{t+1}.

3.3 Econometric Framework

3.3.1 Risk Premium Estimation

This section describes Fama and MacBeth's (1973) two-pass estimation procedure to test risk premia, which this study adopts. This procedure is used to estimate risk premia, λ, and factor beta β_i for portfolio i. The expected excess return for portfolio i is:

$$E[r_i] = \lambda' \beta_i. \tag{3.4}$$

The risk premia, λ, have the same values across portfolios, and β_i is the portfolio i's exposure to risk, which differs across portfolios. The factor betas are estimated by time series regressions, where each portfolio's excess return is regressed on the risk factor h_t:

$$r_{i,t} = \alpha_i + h'_t \beta_i + \epsilon_{i,t} \tag{3.5}$$

where $\epsilon_{i,t}$ is an error term. Burnside (2011) highlights the importance of checking whether betas are statistically and economically significant. The risk premia are then obtained by a cross-sectional regression where the portfolios' time series average excess returns are regressed on the estimated betas $\hat{\beta}_i$:

$$E[r_i] = \lambda' \hat{\beta}_i + \eta_i \tag{3.6}$$

where η_i is an error term. Since these betas are estimated variables, estimation uncertainty should be taken into account for statistical inference. Accordingly, this study follows Burnside (2011) and uses the Shanken (1992) standard errors to account for estimation uncertainty.[5]

3.3.2 Empirical Factor Model

The proposed empirical strategy in examining the importance of commodity prices and other factors is to adopt a data reduction method. This section describes the approach to estimate the empirical factors in the data rich environment. This study estimates three types of common factors: across the entire macro-finance dataset, across all commodity prices, and within a particular group of commodity prices. To this end, this study uses the Dynamic Hierarchical Factor Model (DHFM) proposed by Moench et al. (2013). Conventional empirical factor models that extract factors using principal components have limited flexibility and present a difficulty in interpreting the factors. Instead, if we have some prior knowledge of the data structure, the DHFM can help with the identification of the empirical factor model. Moench et al. (2013) present a four-level model with common, block, subblock and idiosyncratic components, and this study adopts a similar four-level structure. Let $Z_{bkn,t}$ be the time-t observation of the nth series in subblock k, of block b. This is explained by the empirical factor ($H_{bk,t}$) and idiosyncratic variation ($e_{Zbkn,t}$). The four-level factor model is then written as:

$$Z_{bkn,t} = \Lambda_{Hbkn}(L)H_{bk,t} + e_{Zbkn,t} \tag{3.7}$$

$$H_{bk,t} = \Lambda_{Gbk}(L)G_{b,t} + e_{Hbk,t} \tag{3.8}$$

$$G_{b,t} = \Lambda_{Fb}(L)F_t + e_{Gb,t} \tag{3.9}$$

[5]Jagannathan and Wang (1998) point out that the Shanken (1992) standard errors are inappropriate if heteroscedasticity is present. In the Appendix, this study also reports the estimation results by the Generalized Method of Moments (GMM) as in Cochrane (2005).

where $\Lambda_j(L)$, with j=$Hbkn$, Gbk and Fb, is a matrix of the time-invariant lag of loadings, and L is the lag order.[6] The matrix is lower triangular with ones on the diagonal to identify the factors and loadings.[7] The subblock factor $H_{bk,t}$ is the latent factor of subblock k at time t, and it captures the common movement in subblock k. This subblock factor $H_{bk,t}$ contains a block factor $G_{b,t}$ and a subblock-specific variation $e_{Hbk,t}$. Similarly, in equation (3.9) the block factor $G_{b,t}$ contains a common factor F_t and a block-specific variation $e_{Gb,t}$. Using equations (3.8) and (3.9), the relation between the subblock factor $H_{bk,t}$ and the common factor F_t can be written as:

$$H_{bk,t} = \Lambda_{Gbk}(L)\Lambda_{Fb}(L)F_t + \Lambda_{Gbk}(L)e_{Gb,t} + e_{Hbk,t}. \tag{3.10}$$

The first term on the right hand side of equation (3.10) is a time-varying intercept. Moreover, the data series $Z_{bkn,t}$ is linked to the common factor by equations (3.7) and (3.10).

The idiosyncratic subblock-specific and block-specific variations, as well as the common factors, are assumed to be stationary, normally distributed autoregressive processes of order one, and evolve as follows:[8]

$$\begin{aligned}
e_{Zbkn,t} &= \Psi_{Zbkn}e_{Zbkn,t-1} + \epsilon_{Zbkn,t} && (3.11)\\
e_{Hbk,t} &= \Psi_{Hbk}e_{Hbk,t-1} + \epsilon_{Hbk,t} && (3.12)\\
e_{Gb,t} &= \Psi_{Gb}e_{Gb,t-1} + \epsilon_{Gb,t} && (3.13)\\
F_t &= \Psi_F F_{t-1} + \epsilon_{Ft} && (3.14)
\end{aligned}$$

with $\epsilon_{jt} \sim N(0, \sigma_j^2)$, and j=$Zbkn$, Hbk, Gb and F. Ψ_j are AR(1) coefficients and all $\epsilon_{j,t}$ are uncorrelated across j and over t. Prior to estimation, the data is transformed to ensure stationarity using the method of Stock and Watson

[6]This study sets the number of lags to zero as in Moench et al. (2013).

[7]Moench et al. (2013) posit that even in a two-level dynamic factor model, we cannot identify $\Lambda_{Fb}(L)$ and F_t without restrictions.

[8]The DHFM can be set with different lag orders in $e_{Zbkn,t}$, $e_{Hbk,t}$, $e_{Gb,t}$ and F_t.

(2005).[9]

A standard method to estimate latent factors from a large number of data series is principal components. Principal components, however, would not account for potential relations between common and block factors and a time series structure such as that described in equations (3.11) to (3.14). Moench et al. (2013) propose a Markov Chain Monte Carlo (MCMC) method to estimate the factor model.[10] This study employs the MCMC method and discards the first 20,000 draws as burn-in, and saves every 100th of the remaining 50,000 draws.

3.4 Empirical Results

3.4.1 Data

To calculate currency excess returns, daily spot and one-month forward exchange rates against the USD are obtained from Datastream. This data contains bid and ask quotes and end of month values extracted from the daily data series considered by Lustig et al. (2011). The dataset covers the same 37 countries in Lustig et al. (2011), and this study also constructs separate developed country portfolios from emerging country portfolios. The country list is reported in the Appendix.

The monthly dataset extends from February 1983 to December 2013. Since not all series start from February 1983, the total number of exchange rates varies during this period. As data on most of the emerging market exchange rates is available from January 1997, the emerging country portfolios start from January 1997. Following Lustig et al. (2011) and Menkhoff et al. (2012a), the

[9]When this study uses series different from those used by Stock and Watson (2005), it ensures the data is stationary based upon the Augmented Dickey Fuller (ADF) test.

[10]Initial values of the common, block, and subblock factors are estimated by principal components.

older currencies of the Euro member countries are replaced by the Euro after January 1999, and outliers pointed out in Lustig et al. (2011) are deleted.[11]

Next, this study describes the dataset used to estimate the risk factors by the empirical factor model. This study uses the log of real commodity prices, and uses 23 non-fuel commodity prices, and three oil prices. 23 non-fuel commodities are selected based upon the widely used Commodity Price Index of Grilli and Yang (1988). This data is from the IMF and the World Bank, and real commodity prices are computed using the U.S. Consumer Price Index (CPI).[12]

This study also employs a balanced panel of 102 monthly series to test a wide range of information as in Stock and Watson (2005). This study tests whether a common factor across commodity prices and the other macroeconomic data contains useful information in pricing currency carry trades. The motivation is that these estimated factors may capture a wide range of alternative macro and financial factors associated with currency excess returns, as pointed out by Ludvigson and Ng (2007, 2009). In general, this dataset contains the following U.S. macroeconomic series: income, consumption, employment, production, housing starts, producer and consumer prices, interest rates, and money supply. Further, and as reported by Dobrynskaya (2014) and Lettau et al. (2014) that stock market information is linked to currency carry trade risk, this study includes four important potential stock market risk factors, namely market proxy equity index, size, value, and momentum factors, based upon the studies of Fama and French (1993) and Carhart (1997).

This study starts building the DHFM by arranging the data into three blocks: commodity price (COM), finance (FIN) and real economy (ECO). The commodity price block has the following four subblocks: food prices (FOO), agricultural material prices (AGR), metals (MET), and oil (OIL). The finance

[11]This study also pre-treats the dataset using the approach of Darvas (2009) and Cenedese et al. (2014). See the Appendix.

[12]See the dataset in the Appendix.

block has the following three subblocks: stock market (STO), interest rate (INT), and money (MON). The real economy block has the following five subblocks: income and consumption (INC), production (PRO), employment (EMP), house (HOU), and price (PRI). The real economy and the finance blocks are partitioned as in Stock and Watson (2005).[13]

3.4.2 Descriptive Statistics

Table 3.1 provides descriptive statistics of the currency portfolio returns. Panel A contains statistics for all country results. The first and second rows report the annualized mean and standard deviation of excess return, respectively. This study multiplies the average monthly excess return by 12 and the monthly standard deviation by root 12 to obtain annualized values. Portfolio P1 contains the lowest interest rate currencies and portfolio P6 contains the highest interest rate currencies. P6 has the highest average excess return and the highest standard deviation. The return spread between P1 and P6 (i.e., High Minus Low, HML_{FX}) is statistically different from zero at the 10% level. The third and fourth columns show the skewness and kurtosis. High interest portfolios, P5 and P6, have more negative skewness, and this result is similar to that of Menkhoff et al. (2012a) and Dobrynskaya (2014). This negative skewness reflects the unwinding of carry trades, as suggested by Brunnermeier et al. (2009).

The same return pattern is also seen for developed countries in Panel B of Table 3.1. The emerging countries' result in Panel C provides a high HML_{FX}. This result is consistent with Burnside et al. (2007) and Gilmore and Hayashi (2011). The mean excess returns in emerging countries are not monotonically

[13]The Appendix summarises the model structure.

increasing from P1 to P6 and the high trading cost might be the reason, as pointed out by Burnside et al. (2007).

TABLE 3.1: Descriptive Statistics

	P1	P2	P3	P4	P5	P6	HML_{FX}
Panel A: All Countries							
Mean	0.94	-1.19	1.15	2.71*	0.88	4.08*	3.13*
	[0.58]	[-0.71]	[0.78]	[1.78]	[0.47]	[1.90]	[1.85]
Std.dev.	9.17	8.28	8.20	8.20	9.14	10.46	8.35
Skewness	0.16	-0.06	-0.31	-0.29	-0.57	-0.57	-0.55
Kurtosis	4.14	4.19	3.90	4.60	4.97	5.27	5.36
Panel B: Developed Countries							
Mean	1.69	-0.78	0.91	2.64	4.16**		2.48
	[0.90]	[-0.40]	[0.50]	[1.44]	[1.97]		[1.46]
Std.dev.	10.50	9.77	9.49	9.28	10.44		8.94
Skewness	0.20	-0.10	-0.32	-0.22	-0.51		-0.72
Kurtosis	3.46	3.55	3.85	5.27	4.55		5.02
Panel C: Emerging Countries							
Mean	0.40	-1.82	-0.52	-0.90	-4.89	7.35**	6.59**
	[0.22]	[-1.55]	[-0.38]	[-0.44]	[-1.57]	[2.00]	[2.17]
Std.dev.	7.59	4.48	5.65	8.23	12.06	12.15	10.86
Skewness	-0.68	-0.17	-0.78	-0.26	-2.74	-0.85	-0.62
Kurtosis	8.80	4.78	5.44	5.16	19.23	6.24	4.77

Notes: This table reports annualized mean, annualized standard deviations, skewness, and kurtosis of USD excess returns of currency portfolios sorted monthly at $t-1$ by forward discounts. HML_{FX} denotes a portfolio that is long in portfolio 6 (5) and short in portfolio 1. Newey and West (1987) HAC t-statistics are reported in square brackets. *,**, and *** indicate significance at the 10%, 5% and 1% levels, respectively. The sample period of all and developed countries is February 1983 to December 2013. The sample period of emerging countries is January 1997 to December 2013.

3.4.3 Variance Decomposition

Next, this section presents the results of a variance decomposition of the risk factors, which seeks to explain returns. Table 3.2 reports the posterior means and standard deviations of estimated variance shares relative to the total variance as in Moench et al. (2013). $Share_F$ is the variance share of common variations, and $Share_G$, $Share_H$, and $Share_Z$ are the variance shares of block, subblock, and idiosyncratic variations, respectively.

First, the commodity block is explored. A single common factor does not appear to capture the commodity block variation. The block variation is important for oil, explaining 83% of total variance ($Share_G$ is equal to 0.825 for OIL). The subblock variation has a larger share in the agricultural materials and the metals subblocks ($Share_H$ explains 15% and 23%, respectively). This implies that there is a common component in the agricultural materials and the metals subblocks, respectively. The food subblock, in contrast, is largely explained by the idiosyncratic variation ($Share_Z$ has a posterior mean of 0.920 for FOO). These results present evidence of the extent of heterogeneity across different types of commodity groups.

The finance block result is also reported in Table 3.2 and the influence of the common variation is small for this information set. The finance variation is more substantial than the common variation in this group. For instance, the finance variation accounts for 31% of interest rate movements and 18% of the stock market, implying that the main driver of the finance block is the interest rate.

3.4.4 Cross-sectional Results

This section now turns to the core estimation results of the currency excess returns commodity linear factor model in equation (3.6). Table presents the first set of cross-sectional asset pricing test results using the commodity price factors. The estimated risk premia (λ), root mean-squared error (RMSE), and pricing error tests (χ^2 and p-value) are reported. The R^2 are computed by the predicted ($\hat{R}$) and actual mean ($\bar{R}$) excess returns, as in Burnside (2011):

$$R^2 = 1 - \frac{(\bar{R} - \hat{R})'(\bar{R} - \hat{R})}{(\bar{R} - \tilde{R})'(\bar{R} - \tilde{R})} \tag{3.15}$$

TABLE 3.2: Decomposition of Variance

Block	Subblock	$Share_F$	$Share_G$	$Share_H$	$Share_Z$
		Posterior Mean (Standard Deviation)			
COM	FOO	0.001	0.039	0.040	0.920
		(0.001)	(0.015)	(0.015)	(0.030)
COM	AGR	0.001	0.022	0.147	0.831
		(0.001)	(0.011)	(0.062)	(0.069)
COM	MET	0.002	0.068	0.233	0.697
		(0.002)	(0.020)	(0.034)	(0.043)
COM	OIL	0.027	0.825	0.084	0.063
		(0.023)	(0.025)	(0.006)	(0.009)
FIN	STO	0.000	0.182	0.151	0.666
		(0.000)	(0.021)	(0.017)	(0.037)
FIN	INT	0.001	0.312	0.019	0.668
		(0.001)	(0.012)	(0.002)	(0.011)
FIN	MON	0.000	0.001	0.169	0.830
		(0.000)	(0.002)	(0.009)	(0.008)

Notes: This table displays the decomposition of variance based on Moench et al. (2013). $Share_F$, $Share_G$, $Share_H$, and $Share_Z$ denote the average of variance share across all variables in the subblock due to common, block-level, subblock-level and idiosyncratic shocks, respectively. The commodity block has the following four subblocks: food prices (FOO), agricultural material prices (AGR), metals (MET), and oil (OIL). The finance block has the following three subblocks (SB): stock market (STO), interest rate (INT), and money (MON).

where $\tilde{R}$ is the cross-sectional average of the mean excess returns. Excess returns adjusted for the bid-ask spread are used to account for transaction costs, and the cross-sectional model is estimated without a constant term.[14] Burnside (2011) highlights that if the constant term is included, it can account for a large part of the variation and can inflate R^2.

This section begins with the commodity price factors, which represent the main focus of this chapter. This estimation examines whether commodity group information is useful in pricing currency carry trades, and four commodity factors: food, agricultural material, metal, and oil, are compared. In addition, the dollar factor DOL is included as in Lustig et al. (2011) and Menkhoff et al. (2012a). DOL loads onto all portfolios equally, which implies that it represents the average currency excess return for a U.S. investor who invests in foreign currencies.

The results in Table 3.3 Panel A present evidence that the agricultural material ($SB - AGR$) and metal ($SB - MET$) factors can price currency portfolios. Column (1) reports the risk premium of the agricultural material factor to be statistically significant at the 1% level and the impact of the risk premium is 3.4% (=0.30 $\times$ 12) per annum. The high R^2 and the lower RMSE indicate a good model performance. Column (2) indicates that the metal factor has a statistically significant risk premium and its impact is similar to that of the agricultural material factor.[15] To study the agricultural and metal factors further, this study investigates factor exposure of commodity importing and exporting countries. Ready et al. (2016) report that commodity importing and exporting countries have heterogeneous exposure to global productivity shocks. This study replicates the Ready et al. (2016) results in the Appendix, and they

[14]Table B.2 in the Appendix reports results that use currency portfolios without bid-ask spreads as in Ahmed and Valente (2015).

[15]For robustness, the CRB Raw industrial material subindex return, which is used in Bakshi and Panayotov (2013) and IMF agricultural material and metal index returns are also adopted.

indicate that the commodity factors are linked to global production shocks, since commodity importing and exporting countries have opposite exposure to these commodity factors.

The results for the food and oil factors are presented in columns (3) and (4) in Table 3.3. Although the food factor model has a high R^2 and a small RMSE, we interpret these results cautiously because the betas related to this factor are not estimated with high precision, and this study presents evidence of this below in Table 3.5. The oil factor is not associated with the cross-section of currency excess returns. This finding is intuitive, since oil exporting countries, such as Saudi Arabia and Kuwait, are not high interest rate countries.

The results of the finance block factors are presented in Panel B of Table 3.3. As Lettau et al. (2014) and Dobrynskaya (2014) provide evidence that financial market information is linked to currency carry trades, this study tests whether financial factors extracted by the DHFM can price the cross-section of currency portfolios. Column (5) provides the result of the stock market factor ($SB - STO$), which confirms that this factor is related to cross-sectional currency excess returns. The risk premium is statistically significant at the the 1% level and is 3.8% per annum. Dobrynskaya (2014) reports that the CAPM cannot account for currency excess returns, but downside stock market risk is crucial. Since the stock market factor is negatively correlated with stock market volatility innovations, it could be related to downside market risk.[16] The stock market factor, however, is not a simple downside risk factor, because it includes the size, value, and momentum factors of Fama and French (1993) and Carhart (1997). The remaining columns in Panel B report that the other finance subblock factors are less promising than the stock market factor. Finally, column (8) confirms that DOL cannot price cross-sectional currency returns, which is suggested by Lustig et al. (2011).

[16] The correlation between $SB - STO$ and S&P500 volatility innovations is -0.43.

TABLE 3.3: Cross-sectional Asset Pricing: Commodity and Finance Subblocks

Panel A: Commodity Block				
	(1)	(2)	(3)	(4)
	λ	λ	λ	λ
DOL	0.15	0.15	0.15	0.16
	(0.12)	(0.12)	(0.12)	(0.12)
$SB-AGR$	0.30***			
	(0.12)			
$SB-MET$		0.31**		
		(0.12)		
$SB-FOO$			0.87*	
			(0.48)	
$SB-OIL$				1.73
				(1.58)
R^2	0.57	0.53	0.81	0.20
RMSE	0.10	0.11	0.07	0.14
χ^2	11.97**	12.30**	1.69	5.35
[p-value]	[0.02]	[0.02]	[0.79]	[0.25]
Panel B: Finance Block				
	(5)	(6)	(7)	(8)
	λ	λ	λ	λ
DOL	0.15	0.16	0.16	0.16
	(0.12)	(0.12)	(0.12)	(0.12)
$SB-STO$	0.32***			
	(0.11)			
$SB-INT$		-1.17		
		(0.96)		
$SB-MON$			-0.06	
			(0.11)	
R^2	0.85	0.18	0.09	0.09
RMSE	0.06	0.14	0.15	0.15
χ^2	4.88	9.52**	20.11***	22.23***
[p-value]	[0.30]	[0.05]	[0.00]	[0.00]

Notes: This table reports cross-sectional pricing results of the linear factor model based on the commodity prices or financial risk factors. The test assets are excess returns of six carry trade portfolios. The coefficient of factor risk premium λ in equation (3.6) is estimated by the procedure of Fama and MacBeth (1973). Abbreviations of the factor variables are reported in the first column. DOL is the dollar risk factor. $SB-AGR$ is the agricultural material prices, $SB-MET$ is the metal, $SB-FOO$ is the food prices, $SB-OIL$ is the oil, $SB-STO$ is the stock market, $SB-INT$ is the interest rate, and $SB-MON$ is the money factors estimated by the Dynamic Hierarchical Factor Model. Shanken (1992) standard errors are reported in parentheses. The R^2 is a measure of fit between the sample mean and the predicted mean returns. The RMSE is the root of mean-squared error and is reported in percentage points. The χ^2 test statistics of pricing errors are reported and the null hypothesis is that there is no pricing error. p-values are reported in square brackets. *,**, and *** indicate significance at the 10%, 5% and 1% levels, respectively. The sample period is from February 1983 to December 2013.

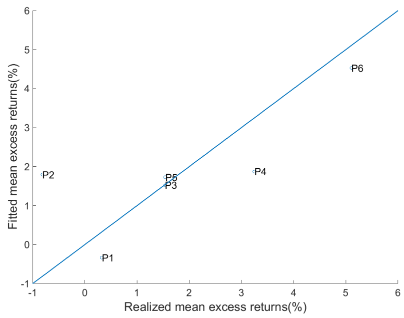
To visualise the results, Figure 3.1 plots the pricing errors of asset pricing models with the DOL and the various empirical factors that this study identifies, as in Menkhoff et al. (2012a). The realized mean currency excess returns are on the x-axes, and the predicted mean currency excess returns by the asset pricing models are on the y-axes. If there is no pricing error, all six portfolios should lie on the 45-degree line. Figure 3.1 Graph A is the agricultural material factor, Graph B is the metal factor, and Graph C is the stock market factor. These graphs show that all portfolios, except P2, plot close to the 45-degrees line with small pricing errors, and these images illustrate the empirical findings.

Given these promising commodity and stock market results, this study next tests whether a common factor across all blocks has information to price currency excess returns. Column (1) in Table 3.4 reports the results of the common factor ($COMMON$). These show that this common factor across the entire dataset is not related to the cross-section of currency excess returns, possibly because the broad common macro-finance factor is not sufficiently granular. For robustness, a common factor is also extracted from across the entire dataset by conventional principal component analysis and the results are reported in column (2). These confirm the conclusions drawn from the results reported in column (1) that commodity and stock market information need to be considered separately.

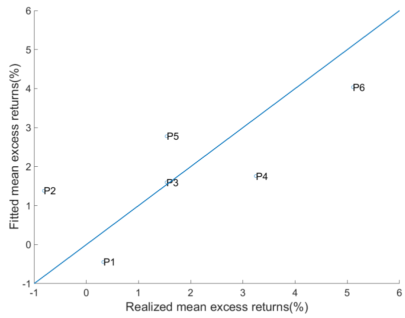
Next, the commodity common factor is tested and column (3) in Table 3.4 presents the results, which also show a weak relationship between this factor and currency excess returns. The main driver of the commodity common factor is the oil subblock as shown in Table 3.2. This weak relationship is consistent with the results in Table 3.3, suggesting that commodity subblock information is more important than common components. This implies

FIGURE 3.1: Pricing error plots

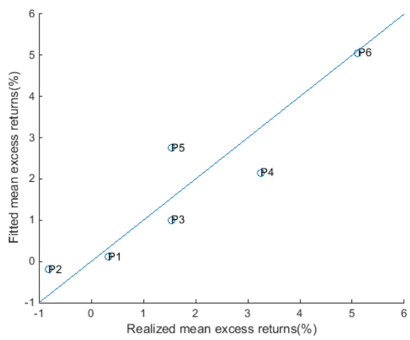
(A) $SB - AGR$



(B) $SB - MET$



(C) $SB - STO$



This figure displays pricing errors for asset pricing models with a combination of DOL and a subblock factor. The realized mean excess returns ($r_{i,t}$) are on the horizontal axis and the mean fitted excess returns are on the vertical axis. Both excess returns are annualized returns. Graph A uses the agricultural material prices subblock ($SB - AGR$), Graph B uses the the metals subblock ($SB - MET$), Graph C uses the stock market ($SB - STO$) factors estimated by the Dynamic Hierarchical Factor Model. The sample period is from February 1983 to December 2013.

that information heterogeneity across commodity blocks is crucial to the cross-sectional asset pricing model. It also implies that commodity prices are linked to a particular country's macro economic state and a country cannot hedge the specific-commodity price risk.

TABLE 3.4: Cross-sectional Asset Pricing: Common Factor

	(1)	(2)	(3)
	λ	λ	λ
DOL	0.16	0.16	0.16
	(0.12)	(0.12)	(0.12)
$COMMON$	0.10		
	(0.16)		
$PCAF_1$		0.15	
		(0.31)	
$B-COM$			0.48
			(0.30)
R^2	0.10	0.09	0.42
RMSE	0.15	0.15	0.12
χ^2	20.58***	20.03***	5.96
[p-value]	[0.00]	[0.00]	[0.20]

Notes: This table reports cross-sectional pricing results of the linear factor model based on the common risk factors. The test assets are excess returns of six carry trade portfolios. The coefficient of factor risk premium λ in equation (3.6) is estimated by the procedure of Fama and MacBeth (1973). Abbreviations of the factor variables are reported in the first column. DOL is the dollar risk factor. $COMMON$ is the common and $B-COM$ is the commodity factors estimated by the Dynamic Hierarchical Factor Model. $PCAF_1$ is the common factor obtained by a principal component. Shanken (1992) standard errors are reported in parentheses. The R^2 is a measure of fit between the sample mean and the predicted mean returns. The RMSE is the root of mean-squared error and is reported in percentage points. The χ^2 test statistics of pricing errors are reported and the null hypothesis is that there is no pricing error. p-values are reported in square brackets. *,**, and *** indicate significance at the 10%, 5% and 1% levels, respectively. The sample period is from February 1983 to December 2013.

3.4.5 Time Series Results

This section conducts time series analyses on the factors identified above. If a factor can account for currency excess returns, currency portfolios should have significant exposure to this factor over time. The currency excess returns are regressed on a constant, DOL, and the agricultural material, metal, food, and stock market factors. The results are reported in Table 3.5. Panel A reports the results using the agricultural factor. All estimated values of β_{DOL} are around one and significant at the 1% level. All portfolios have almost the same exposure to DOL, which is a result that is consistent with Lustig et al. (2011). The estimated betas on the agricultural material factor, β_{AGR} are statistically significant at the 1% level for P1 and P6. The negative coefficient of P1 and the positive risk premium imply that the lowest interest rate portfolio acts as a hedge against agricultural material risk. This study also considers the economic impact of this factor. Since the standard deviation of the agricultural factor is 0.39, a one-standard-deviation change in the agricultural material factor would reduce the annualized excess return of P1 by 2.9% and increase that of P6 by 3.3%, all else equal.[17]

The results of the metal factor in Panel B of Table 3.5 have a similar pattern to those of the agricultural material factor. Interestingly, the estimated parameters β_{MET} increase monotonically from P1 to P6, and those for P1 and P6 are statistically significant at the 1% and the 5% levels, respectively. In contrast, Panel C provides evidence that all factor betas on the food factor, β_{FOO}, are insignificant. This suggests that the factor betas used in the cross-sectional asset pricing model in Table 3.3 are not estimated with precision, because the betas using the cross-sectional regression in Table 3.3 have a weak relation with the food factor.

Finally, the results on the stock market factor are presented in Panel D. Apart from P1, the estimates of the coefficient on the stock market factor, β_{STO}, increase monotonically from -0.49 for P2 to 0.78 for P6. P1, P2 and P6 have statistically significant betas. As the risk premium on the stock market factor is positive, as shown in Table 3.4, this result means P1 and P2 act as hedges against stock market risk. The standard deviation of the stock market factor

[17]This result is not reported in the table.

TABLE 3.5: Time Series Results

Panel A: Factor Betas: $SB-AGR$					Panel B: Factor Betas: $SB-MET$				
P	α	β_{DOL}	β_{AGR}	adjR^2	P	α	β_{DOL}	β_{MET}	adjR^2
1	-0.13*	1.02***	-0.62***	0.77	1	-0.14**	1.03***	-0.63***	0.77
	(0.07)	(0.05)	(0.24)			(0.07)	(0.05)	(0.23)	
2	-0.21***	0.93***	0.02	0.80	2	-0.21***	0.93***	-0.09	0.80
	(0.06)	(0.05)	(0.19)			(0.06)	(0.04)	(0.18)	
3	-0.02	0.97***	-0.07	0.88	3	-0.02	0.97***	-0.05	0.88
	(0.04)	(0.02)	(0.11)			(0.04)	(0.02)	(0.10)	
4	0.13***	0.93***	0.04	0.83	4	0.13***	0.94***	0.01	0.83
	(0.05)	(0.03)	(0.14)			(0.05)	(0.03)	(0.14)	
5	-0.03	1.03***	-0.05	0.84	5	-0.02	1.02***	0.02	0.84
	(0.05)	(0.03)	(0.15)			(0.06)	(0.03)	(0.15)	
6	0.26***	1.12***	0.69***	0.76	6	0.26***	1.11***	0.53**	0.76
	(0.08)	(0.04)	(0.24)			(0.08)	(0.04)	(0.24)	

Panel C: Factor Betas: $SB-FOO$					Panel D: Factor Betas: $SB-STO$				
P	α	β_{DOL}	β_{FOO}	adjR^2	P	α	β_{DOL}	β_{STO}	adjR^2
1	-0.12*	1.01***	-0.23	0.77	1	-0.13*	1.01***	-0.44***	0.76
	(0.07)	(0.04)	(0.20)			(0.07)	(0.05)	(0.22)	
2	-0.21***	0.93***	-0.14	0.80	2	-0.22***	0.94***	-0.49***	0.80
	(0.06)	(0.04)	(0.21)			(0.06)	(0.04)	(0.19)	
3	-0.02	0.96***	0.09	0.88	3	-0.02	0.97***	-0.19	0.88
	(0.04)	(0.02)	(0.10)			(0.04)	(0.02)	(0.13)	
4	0.13***	0.93***	0.13	0.83	4	0.13***	0.93***	0.19	0.83
	(0.05)	(0.03)	(0.12)			(0.05)	(0.04)	(0.15)	
5	-0.03	1.03***	-0.08	0.84	5	-0.03	1.03***	0.23	0.84
	(0.05)	(0.03)	(0.13)			(0.05)	(0.03)	(0.15)	
6	0.25***	1.13***	0.21	0.76	6	0.26***	1.12***	0.78***	0.76
	(0.09)	(0.04)	(0.21)			(0.08)	(0.04)	(0.24)	

Notes: This table presents of time series regressions of excess returns of carry trade portfolios on a constant (α), the dollar risk (DOL), and subblock factors. $SB-AGR$ is the agricultural material prices, and $SB-MET$ is the metal, $SB-FOO$ is the food prices, and $SB-STO$ is the stock market factors estimated by the Dynamic Hierarchical Factor Model. The standard errors are reported in parentheses and obtained by the Newey and West (1987) procedure with optimal lag selection according to Andrews (1991). The adjusted R^2 are also reported. *,**, and *** indicate significance at the 10%, 5% and 1% levels, respectively. The sample period is from February 1983 and December 2013.

is 0.35 and if the stock market factor changes by one standard deviation, the annualized excess return to P1 increases by 1.9% and the annualized excess return to P6 decreases by 3.3%. This implies that the betas on the stock market factor have an economically significant impact on excess returns of currency portfolios.

TABLE 3.6: Time Series Regression with HML_{FX}

	AGR	MET	AGR^{orth}	MET^{orth}	STO	STO^{orth}	ΔVOL_{FX}	adjR^2
(1)	1.40***							0.05
	(0.42)							
(2)		1.28***						0.04
		(0.43)						
(3)	1.18***						-7.23***	0.15
	(0.32)						(1.29)	
(4)		0.87***					7.02***	0.13
		(0.31)					(1.32)	
(5)	1.19***			0.49			-6.90***	0.15
	(0.31)			(0.31)			(1.24)	
(6)		0.87***	1.00***				-6.90***	0.15
		(0.28)	(0.34)				(1.21)	
(7)	1.20***					0.87***	-6.69***	0.17
	(0.31)					(0.32)	(1.24)	
(8)		0.89***				0.78**	-6.60***	0.14
		(0.30)				(0.33)	(1.26)	
(9)			1.17***		0.92***		-6.70***	0.17
			(0.31)		(0.32)		(1.24)	
(10)				0.78***	0.93***		-6.60***	0.14
				(0.33)	(0.30)		(1.25)	

Notes: This table shows results for time series regressions of HML_{FX} on a constant and factors. HML_{FX} is the high minus low currency portfolios as in Lustig et al. (2011). AGR is the agricultural material prices, MET is the metal, and STO is the stock market factors estimated by the Dynamic Hierarchical Factor Model. This table also investigates the orthogonal factors, based upon Menkhoff et al. (2012a). AGR^{orth} is the orthgonalized agricultural material prices, MET^{orth} is the orthgonalized metal, and STO^{orth} is the orthgonalized stock market factors. ΔVOL_{FX} is the global FX volatility innovations as in Menkhoff et al. (2012a). The estimated coefficient for the constant term are not reported. The standard errors are reported in parentheses and obtained by the Newey and West (1987) procedure with optimal lag selection according to Andrews (1991). The adjusted R^2 are also reported. *,**, and *** indicate significance at the 10%, 5% and 1% levels, respectively. The sample period is from February 1983 and December 2013.

Given the strong relationship between high and low interest rate currency portfolios, and the commodity factors, this study conducts a further analysis to explore the relationship with HML_{FX}. HML_{FX} has been used in the cross-sectional literature to identify carry returns. HML_{FX} is computed as the return spread between high and low currency portfolios, and Lustig et al. (2011) links this popular factor to global stock market risk. The relationship with commodity prices, however, has not been investigated in the literature. This study regresses HML_{FX} on the agricultural material and metal factors. Rows (1) and (2) in Table 3.6 are the base results, and both agricultural material and metal factors are significant at the 1% level and the economic impacts are large. For instance, one standard deviation change in the agricultural material leads to 6.6% change in HML_{FX}. This study also controls for the effect of the global FX volatility innovations (ΔVOL_{FX}) of Menkhoff et al. (2012a) in rows (3) and (4). The magnitude reduces slightly, but both coefficients remain statistically significant at the 1% level.

Next, this study tests which of the two factors is more important for HML_{FX} in rows (5) and (6) in Table 3.6. As the agricultural material and metal factors are correlated, the metal factor is orthogonalized to the agricultural material factor in row (5), which is the same approach of Menkhoff et al. (2012a). Now, the orthogonalized metal factor, MET^{orth}, becomes insignificant. In contrast, the orthogonalized agricultural material factor, AGR^{orth}, remains significant at the 1% level in row (6). These results imply that the agricultural material factor drives out the metal factor. This study also compares the commodity factors and the IMF index in the Appendix and the results confirm that the proposed commodity factors have a dominant effect.

Finally, this study examines whether the commodity factors remain significant with the stock market factor. The stock market factor is orthogonalized to the agricultural material and metal factors in rows (7) and (8). This study repeats the opposite operations in rows (9) and (10).[18] These results show that the commodity and stock market factors have different information, and both are highly associated with HML_{FX}. Hence the proposed approach in this chapter is useful in explaining the time series movement in the widely cited HML_{FX} for carry returns.

A possible explanation for the difference between commodity and stock market information is that the former is mainly related to emerging currencies and the latter is tied to currencies in advanced economies. The previous literature does not point out this difference and focuses on the common risk. For instance, Lustig et al. (2011) propose a theoretical approach based upon a no-arbitrage model, and the key assumption is that each currency has a different exposure to a common shock. They use stock market volatility as a proxy for the common shock. Subsequent empirical studies support this assumption and demonstrate that downside stock market is an important risk factor for carry trades (e.g., Atanasov and Nitschka, 2014; Dobrynskaya, 2014 and Lettau et al. 2014). However, some emerging countries' currencies may not be tied to world financial market risk, perhaps because they do not have highly developed nor globally integrated financial markets. In fact, Habib and Stracca (2012) show that a reversal of carry trades during the financial crisis has a clear pattern only in liquid currencies. For the less liquid currencies of emerging countries, commodity prices instead are more important determinants of exchange rates. Bodart et al. (2012) focus on emerging countries that are dependent upon the export of a single commodity good and find that when commodity prices increase, the currencies appreciate. Hence, commodity price information is strongly linked to emerging currencies, while these currencies'

[18]For further robustness, the world stock market volatility innovations are used in Table B.6 in the Appendix.

link to stock market information is rather weak. The next section investigates this further and tests whether the stock market and commodity factors price both developed and emerging currencies' portfolios.

3.5 Developed and Emerging Portfolios

Given evidence of the heterogeneous information contents of the commodity and stock market factors presented in Table 3.6, this section explores whether they are linked to financial market development. To this end, this section splits the currency dataset into developed country currencies and emerging country currencies. Lustig et al. (2011) use the same developed country dataset as a robustness check. An emerging country category is also considered, since some emerging countries are commodity exporters and commodity prices may affect their interest rates and exchange rates.

Panel A in Table 3.7 reports estimates of risk premia on carry returns of currencies that belong to developed countries. The results in column (1) show that the agricultural material factor cannot price developed country portfolios. In contrast, columns (2) and (3) show that the metal and stock market factors can. This suggests that metal prices are related to the U.S. stock market, as pointed out by Fama and French (1988). This result does not mean that both factors contain the same information, because the previous section provides evidence that the metal factor remains significant while controlling for the stock market factor.

This section turns to the emerging country results in Panel B of Table 3.7. The results in column (4) show that agricultural materials can price the emerging currency portfolios. Surprisingly, the risk premia on the stock market and the metal factors vanish in columns (5) and (6). This implies that a risk factor for developed country currencies differs from that for emerging currencies,

TABLE 3.7: Cross-sectional Asset Pricing: Developed and Emerging Currencies

Panel A: Developed Countries			
	(1)	(2)	(3)
	λ	λ	λ
DOL	0.17	0.17	0.17
	(0.13)	(0.13)	(0.13)
$SB-AGR$	0.06		
	(0.11)		
$SB-MET$		0.27**	
		(0.13)	
$SB-STO$			0.24**
			(0.10)
R^2	0.04	0.56	0.70
RMSE	0.15	0.10	0.08
χ^2	15.12***	6.35*	4.26
[p-value]	[0.00]	[0.10]	[0.23]
Panel B: Emerging Countries			
	(4)	(5)	(6)
	λ	λ	λ
DOL	0.04	0.09	0.08
	(0.13)	(0.13)	(0.13)
$SB-AGR$	0.67**		
	(0.33)		
$SB-MET$		0.12	
		(0.13)	
$SB-STO$			0.10
			(0.26)
R^2	0.49	0.07	0.07
RMSE	0.24	0.32	0.32
χ^2	4.82	24.80***	25.43***
[p-value]	[0.31]	[0.00]	[0.00]

Notes: This table reports cross-sectional pricing results of the linear factor model based on the commodity prices or financial risk factors. The test assets are excess returns of five developed country carry trade portfolios or six emerging country carry trade portfolios. The coefficient of factor risk premium λ in equation (3.6) is estimated by the procedure of Fama and MacBeth (1973). Abbreviations of the factor variables are reported in the first column. DOL is the dollar risk factor. $SB-AGR$ is the agricultural material prices, $SB-MET$ is the metal, and $SB-STO$ is the stock market factors estimated by the Dynamic Hierarchical Factor Model. Shanken (1992) standard errors are reported in parentheses. The R^2 is a measure of fit between the sample mean and the predicted mean returns. RMSE is the root of mean-squared error and is reported in percentage points. The χ^2 test statistics of pricing errors are reported and the null hypothesis is that there is no pricing error. p-values are reported in square brackets. *,**, and *** indicate significance at the 10%, 5% and 1% levels, respectively. The sample period in developed countries is from February 1983 to December 2013 and that in emerging countries is from January 1997 to December 2013.

and that developed countries are connected to stock market risk. This link is intuitive, since developed country currencies are more liquid, and investors usually implement carry trades using mainly developed country currencies. Jylhä and Suminen (2011) find money flows to hedge funds are related to carry trade returns in developed countries. The result also implies that stock and commodity markets risks may be somewhat segmented. This conclusion is consistent with Gorton and Rouwenhorst (2006), who find a low correlation between equity and commodity market returns.

In summary, this study finds the agricultural material factor is strongly related to emerging countries, and the stock market and metal factors are mainly affected by advanced economies. This heterogeneity comes from developed country currencies, which are more liquid and regarded as an investable asset class.

3.6 Conclusion

This chapter investigates a range of commodity price risk factors for portfolios of currency carry trades. Commodity exporting and importing are related to interest rates, as shown by Ready et al. (2016) in advanced economies. Moreover, several high interest rate emerging countries are commodity exporters, thus, commodity prices may affect currency carry trade returns. This chapter focuses on common information across commodity prices and within a certain type of commodity. Since the importance of commodity common information have been investigated recently (e.g., Byrne et al., 2013; Gospodinov and Ng, 2013; Alquist and Coibion, 2014 and West and Wang, 2014), this study extracts common factors from overall commodity prices, and from specific commodity groups. In addition, this study explores the common factor between commodity prices and other macroeconomic data. The motivation in using an empirical factor model is related to Ludvigson and Ng (2007, 2009), who show that empirical factors extracted from a large data set contain richer information. This study also adopts a recently developed factor model to overcome the identification issue of a simple principal component. This model, developed by Moench et al. (2013), has a hierarchical structure that captures common components across data and within the sub-categories of the data.

This study finds commodity prices are important risk factors for the returns of currency carry trades. Although Bakshi and Panayotov (2013) link a commodity price index with future currency excess returns, this study focuses on the cross-sectional relation between currency excess returns and commodity risk factors. This study finds agricultural and metal factors are related to currency trade risk, but broad commodity and oil price factors fail to explain currency excess returns. These heterogeneous results support the use of the dynamic hierarchical factor model.

This study presents evidence that the agricultural material factor is linked to currencies of emerging countries and the metal factor is related to currencies of developed countries. Although stock market information is important in pricing currency carry trades, as shown by Dobrynskaya (2014) and Lettau et al. (2014), this chapter reveals that this information is weakly associated with emerging currencies. This study finds commodity information is a more dominant factor for emerging currencies, since emerging countries do not have liquid financial markets and, hence, are somewhat segmented from world financial market risk. This result is supported by the finding of Habib and Stracca (2012) who present a significant reversal of carry trades during the financial crisis only in developed markets. The findings are important, since the previous literature focuses on the common risk among developed and emerging markets while this study focuses on heterogeneity between these markets. The results call for further research into theoretical models that link commodity price risk to financial market risk.

Chapter 4

Currency Carry Trades and the Conditional Factor Model

4.1 Introduction

A currency portfolio approach sorts currencies based on cross-sectional differences of characteristics such as forward discounts, past returns, and other macroeconomic variables.[1] In particular, currency carry trades, which sort currencies based on forward discounts, are widely explored in the literature (e.g., Burnside et al., 2011; Lustig et al., 2011; Menkhoff et al., 2012a; Atanasov and Nitschka, 2015). Most studies show that currency carry trades yield an average positive return over a long sample, and the explanatory power of risk factors has been explored in a cross-sectional context. For instance, durable and non-durable consumption growth (Lustig and Verdelhan, 2007), carry factor (Lustig et al. 2011), and FX volatility innovations (Menkhoff et al., 2012a) are found to price carry portfolios. These studies assume that alphas and betas are constant. However this assumption may be excessively restrictive. The exchange rate literature shows that a relationship between exchange rates and macro fundamentals is unstable in time series contexts (e.g., Sarno and Valente, 2009;

[1]See Lustig and Verdelhan (2007), Menkhoff et al. (2012b), and Sarno and Schmeling (2014).

Bacchetta and Wincoop, 2013; Rossi, 2013; Byrne et al., 2016). The scape-goat theory is a popular approach to explain this time-varying relationship, see Bacchetta and Wincoop (2013). Hence introducing time-varying alphas and betas may also be beneficial to model the time series behaviour of carry portfolio returns.

This chapter investigates time variations of alphas and factor betas of currency carry portfolios. To this end, this chapter employs a conditional factor model often used in the stock market literature. The conditional factor model assumes that factor betas are dependent upon state variables. If the expected return of the stock market varies over the business cycle, betas also vary to reflect available information for an investor at any given point. For instance, Jagannathan and Wang (1996) use the yield spread of bonds as the state variable, Cochrane (1996) employs the term premium and the dividend-price ratio, and Lettau and Ludvigson (2001) adopt the consumption-wealth ratio.[2] However, this approach is questioned by Lewellen and Nagel (2006), who state that there is a need for "$\cdots$ the econometrician to know the "right" state variable". An econometrician may not know the full set of information that an investor employs for her investment decisions. To avoid this state variable problem, Lewellen and Nagel (2006) evenly divide their sample of stock returns and estimate monthly and quarterly betas using daily data. Each month (quarter) has a different beta and this difference reflects a change in an economic state. Several studies extend Lewellen and Nagel's (2006) approach to nonparametric methods when assessing the importance of risk factors for asset prices. For example, Li and Yang (2011) and Ang and Kristensen (2012) employ a kernel function to estimate a conditional factor model when examining stock market returns. Li and Yang (2011) present empirical evidence that conditional alphas

[2]Another approach is to consider a factor beta as a stochastic variable. See Ang and Chen (2007).

estimated by the nonparametric approach differ from those of the rolling window approach. Ang and Kristensen (2012) report that the conditional alphas of the Capital Asset Pricing Model (CAPM) are constant, while the conditional betas vary over time.

Motivated in part by research on equity markets' conditional factor models, this chapter contributes to the carry trade literature on three fronts. First, this chapter applies a nonparametric conditional factor model in currency carry trades. Few studies investigate currency carry trades using conditional factor models. Atanasov and Nitschka (2014), Dobrynskaya (2014), and Lettau et al. (2014) use them in the currency carry trade context, while all three focus on downside stock market risk. Christiansen et al. (2011) propose a smooth transition model in currency carry trades and the factor beta is dependent on FX market volatility. None of these studies however adopt a nonparametric approach. A nonparametric model has the following advantages. A smooth change in a factor beta is supported by Ghysels (1998). He compares the unconditional and the conditional CAPM using state variables and a parametric model, and observes that the conditional CAPM estimated by the parametric model tends to overestimate time variation of betas. Furthermore, the nonparametric approach is more robust to misspecification problems, as pointed out by Harvey (2001) and Wang (2003). Harvey (2001) demonstrates that when portfolio returns respond to the market return asymmetrically, the conditional expected return estimated by the linear model has low explanatory power. Wang (2003) uses a Stochastic Discount Factor (SDF) approach and a nonparametric model. He shows that the conditional CAPM creates smaller pricing errors than the unconditional CAPM. The contrast between the results of Ghysels (1998) and Wang (2003) suggests that the nonparametric approach is promising for estimating conditional factor models.

The second contribution is to extend Uncovered Interest rate Parity (UIP) studies using a currency portfolio approach. Previous studies focus on economic states when UIP is satisfied, but do not employ the portfolio approach. Bansal (1997) argues that interest differences between home and foreign countries and changes in exchange rates have a nonlinear relationship. He presents empirical evidence that deviations from UIP are observed only when the U.S. interest rate exceeds foreign interest rates. Bansal and Dahlquist (2000) find a similar pattern over a larger number of currencies through the use of panel analysis. More advanced econometrics approaches are also employed in the literature. Baillie and Kilic (2006) apply the Logistic Smooth Transition Auto-Regressive model and find that deviations from UIP are dependent upon the regime. Baillie and Kim (2015) use nonparametric methods and report that violations of UIP are time dependent. In general, these findings all suggest that profitability of carry trades may be time-varying and dependent upon changing economic states. Motivated by this literature this chapter investigates time variations and state dependence in the factor models proposed in the carry trade literature. This chapter adopts a nonparametric conditional factor model to capture time-varying profitability driven by economic states and to avoid the misspecification problem. To keep the analysis tractable and focused, this chapter concentrates on the two most popular factors for explaining carry returns, the dollar factor (DOL) and innovations of global FX volatility (ΔVOL_{FX}). Lustig et al. (2011) propose DOL as a factor that represents the average return for U.S. investors who invest in foreign currencies. This factor accounts for time series fluctuations of currency portfolios. Menkhoff et al. (2012a) show that a high interest rate currency portfolio has a negative beta to ΔVOL_{FX}. The important difference from these studies and this chapter is that this chapter estimates alphas and betas by the conditional model and the nonparametric method.

The third contribution is to explore relations between conditional estimators and a wide range of state variables. Ang and Kristensen (2012) investigate the relation between conditional betas and state variables in the stock market. In addition to well known state variables such as the short interest rate and the term spread, this chapter includes several possible state variables that have not been investigated by Ang and Kristensen (2012). The new state variables are related to global FX volatility and liquidity. This chapter adopts the liquidity measure proposed by Corwin and Schultz (2012). Karnaukh et al. (2015) show that this measure replicates liquidity measures computed from high-frequency FX market data. The Corwin and Schultz measure has merit, in that it can be computed without resorting to high-frequency and order flow data. By applying this measure this chapter is also able to study a longer period and a wide range of currencies.

This chapter finds that the conditional alphas and betas on the dollar and global FX volatility innovations vary over time. The empirical evidence presents statistically significant alphas that are not observed by the conventional approach. The conditional alphas of a one-factor model are strongly related to economic states. When the economy is in a bad state, the alpha of the low interest rate currency portfolio increases while that of the high interest rate currency portfolio decreases. This pattern in the high interest rate portfolio becomes weak when the effect of FX market volatility is controlled for. This chapter also finds that the conditional beta on the dollar is linked to the short term U.S. interest rate and to FX market volatility in the high interest rate currency portfolio. In addition, the FX market liquidity measure is somewhat correlated with this beta. Further, the conditional beta on the FX volatility innovations is associated with the term and the TED spreads.

The remainder of Chapter 4 is organized as follows: Section 4.2 describes the conditional factor model and the estimation method, Section 4.3 presents the data, Section 4.4 discusses the empirical results, and Section 4.5 concludes.

4.2 Methodology

4.2.1 Conditional Factor Model

This section begins setting out a nonparametric approach to estimate a conditional factor model. Let $ret_{i,t}$ be the excess return of currency portfolio i, for M portfolios at time t, and $f_t = (f_{1,t}, \cdots, f_{j,t})$ be j common tradable factors. The excess return is represented by following conditional factor model:

$$ret_{i,t} = \alpha_{i,t} + \beta_{i,t}^{'} f_t + \epsilon_{i,t} \tag{4.1}$$

where $\alpha_{i,t}$ is the time-varying conditional alpha and $\beta_{i,t} = (\beta_{i1,t}, \cdots, \beta_{ij,t})$ is the vector of time-varying factor loadings (betas) for portfolio i. The vector of error terms $\epsilon_t = (\epsilon_{1,t}, \cdots, \epsilon_{M,t})$ has conditional expectation $E[\epsilon_t \mid f_t, \beta_{i,t}] = 0$ and conditional variance $E[\epsilon_{i,t}^2 \mid f_t, \beta_{i,t}] = \Omega_t$. Following Ang and Kristensen (2012), this study introduces τ to adopt a kernel regression, and $\alpha_{i,\tau}$ and $\beta_{i,\tau}$ at any point τ in the interval $1 \leq \tau \leq T$ are obtained by minimizing the following local kernel-weighted least-squared residuals:

$$[\hat{\alpha}_{i,\tau}, \hat{\beta}_{i,\tau}^{'}]^{'} = \arg\min_{(\alpha,\beta)} \sum_{t=1}^{T} K_{h_i T}(t-\tau)(ret_{i,t} - \alpha_i - \beta_i^{'} f_t)^2 \tag{4.2}$$

where $K_{h_i T} = K(z/(h_i T))/(h_i T)$ with $K(\cdot)$ being a kernel with bandwidth $h_i > 0$. The Gaussian kernel is chosen, which is widely used in the finance literature (see, e.g., Ang and Kristensen, 2012; Adrian et al., 2015). $\hat{\alpha}_{i,\tau}$ and $\hat{\beta}_{i,\tau}$ are obtained by solving equation (4.2). The conditional variance of the factors,

$\hat{\Lambda}_\tau$, and the conditional variance of the residual, $\hat{\Omega}_\tau$, are given by:

$$\hat{\Lambda}_\tau = \frac{1}{T}\sum_{t=1}^{T} K_{h_iT}(t-\tau) f_t f_t' \text{ and } \hat{\Omega}_\tau = \frac{1}{T}\sum_{t=1}^{T} K_{h_iT}(t-\tau)\hat{\epsilon}_t\hat{\epsilon}_t' \tag{4.3}$$

This study needs to choose bandwidths to solve equation (4.2). Kristensen (2012), and Ang and Kristensen (2012) employ a 'plug-in' method to select the bandwidths, since cross-validation procedures may provide extremely small bandwidths.[3]

4.2.2 Long-run Alpha and Beta

This study tests whether or not the long-run alpha and beta are constant. The estimated long-run alpha, $\hat{\alpha}_{LR,i}$, and beta, $\hat{\beta}_{LR,i}$, are obtained by the point-wise kernel estimators $\hat{\alpha}_{i,t}$ and $\hat{\beta}_{i,t}$ in equation (4.2):

$$\hat{\alpha}_{LR,i} = \frac{1}{T}\sum_{t=1}^{T}\hat{\alpha}_{i,t},\ \hat{\beta}_{LR,i} = \frac{1}{T}\sum_{t=1}^{T}\hat{\beta}_{i,t}. \tag{4.4}$$

Let $\hat{\alpha}_{LR} = (\hat{\alpha}_{LR,1}, \cdots, \hat{\alpha}_{LR,M})'$ and $\hat{\beta}_{LR} = (\hat{\beta}_{LR,1}, \cdots, \hat{\beta}_{LR,M})'$. Theorem 2 in Ang and Kristensen (2012) shows that, as $T \to \infty$ the long-run estimators $\hat{\alpha}_{LR}$ and $\hat{\beta}_{LR}$ satisfy:

$$\sqrt{T}(\hat{\alpha}_{LR} - \alpha_{LR}) \sim N(0, \Omega_{LR,\alpha\alpha}),\ \sqrt{T}(\hat{\beta}_{LR} - \beta_{LR}) \sim N(0, \Omega_{LR,\beta\beta}) \tag{4.5}$$

where $\alpha_{LR} = E[\alpha_t]$, $\beta_{LR} = E[\beta_t]$, $\Omega_{LR,\alpha\alpha} = E[\Omega_t]$, $\Omega_{LR,\beta\beta} = E[\Lambda_t^{-1} \otimes \Omega_t]$, and $\otimes$ is the Kronecker product. Note that the long-run estimators converge at standard parametric rates, $\sqrt{T}$, instead of slower nonparametric rates, $\sqrt{Th_i}$.

To obtain the bandwidth for the long-run estimator in equation (4.4), this study adjusts the bandwidth h_i in equation (4.2). Since the long-run estimator

[3] The plug-in method is explained in the Appendix.

is described as an integral, it is over-smoothed when the plug-in bandwidth is adopted. Ang and Kristensen (2012) propose the bandwidth for long-run estimator, $h_{LR,i}$, as:

$$\hat{h}_{LR,i} = \hat{h}_i \times T^{-2/15} \tag{4.6}$$

where $\hat{h}_i$ is the estimated bandwidth by the plug-in method.

4.2.3 Constancy Test

Next, this section describes the constancy test of alpha and beta. This section focuses on the test of alpha, since that of beta is similar. The null hypothesis is $H_0 : \alpha_{i,t} = \alpha_i$ for all $t \in [0, T]$. This study employs a F-type test proposed by Ang and Kristensen (2009) and Kristensen (2012) in the stock market and macroeconomic variable contexts, respectively. This study defines the residuals under H_0 as $\tilde{\epsilon}$, and those under H_A as $\hat{\epsilon}$, respectively:

$$H_0 : \tilde{\epsilon}_t = ret_{i,t} - \hat{\alpha}_i - \hat{\beta}'_{i,t} f_t, \quad H_A : \hat{\epsilon}_t = ret_{i,t} - \hat{\alpha}_{i,t} - \hat{\beta}'_{i,t} f_t \tag{4.7}$$

where $\hat{\alpha}_i$ is the semiparametric estimator.[4] The sums of rescaled squared residuals (SSR) are computed under each hypothesis:

$$SSR_0 = \sum_{t=1}^{T} \tilde{z}'_{i,t} \tilde{z}_{i,t}, \quad SSR_A = \sum_{t=1}^{T} \hat{z}'_{i,t} \hat{z}_{i,t} \tag{4.8}$$

where $\tilde{z}_{i,t}$ and $\hat{z}_{i,t}$ are rescaled residuals described by: $\tilde{z}_{i,t} = \hat{\Omega}_{ii,t}^{-1/2} \tilde{\epsilon}_t$ and $\hat{z}_{i,t} = \hat{\Omega}_{ii,t}^{-1/2} \hat{\epsilon}_t$. The F test statistic is derived using the SSR_0 and SSR_A:

$$F_i = \frac{T}{2} \frac{SSR_0 - SSR_A}{SSR_A}. \tag{4.9}$$

[4]More detail is provided in the Appendix.

This test statistic satisfies: $F_i \to \chi^2_{q\mu}/q$. For Gaussian kernels, $q = 2.5375$ and $\mu = 2Mc/h_i$ where M is the number of portfolios, $c = 0.7737$, and h_i is the bandwidth obtained by the plug-in method.

4.3 Data

4.3.1 Currency Portfolios

This chapter focuses on two data sets: "All Countries" and "Developed Countries" with the latter being a subset of the former as in Lustig et al. (2011) and Menkhoff et al. (2012a). In contrast with these two studies, however, this study computes currency carry returns using daily rather than monthly returns, since a conditional factor model benefits from more information in a dataset. Following Christiansen et al. (2011), daily one-day money market rates and spot exchange rates are used.[5] Some countries, that include those in the Menkhoff's et al. (2012a) dataset, do not have one day or one week money market rates, hence the "All Countries" dataset contains 38 countries. The "Developed Countries" dataset includes the same 15 countries of Lustig et al. (2011) and Menkhoff et al. (2012a). The overall sample covers the period from January 2nd 1989 to August 31st, 2015.

A carry trade return is defined by a lagged interest difference and a change in a spot exchange rate. Assuming that our home country is the U.S., the interest difference is computed relative to the U.S. interest rate. The spot exchange rate is defined as the foreign currency per unit of the U.S. dollar. The carry trade return, $ret_{j,d+1}$, is defined as the lagged interest rate differential minus

[5]When a one day money market rate is not available, this study uses a one week money market rate as in Christiansen et al. (2011).

the change in the spot exchange rate, see Christiansen et al. (2011):

$$ret_{j,d+1} = i_{j,d} - i_{us,d} - (s_{j,d+1} - s_{j,d}) \tag{4.10}$$

where $i_{j,d}$ is the interest rate of country j at day d, $s_{j,d}$ is the log of the spot exchange rate of country j at day d, and the end-of-day spot rate is used. This study sorts currencies into five portfolios based on their forward discount, which is the difference between the forward and the spot exchange rates. This study uses the end of the month forward discounts, and the portfolio is constructed at a monthly frequency. The return of the currency portfolio is computed as the average return of all currencies within the portfolio.

4.3.2 Risk Factors

This chapter employs one and two factor models. The dollar (DOL) proposed by Lustig et al. (2011), is used in the one factor model. This risk factor is computed as the average of all currency excess returns. It represents the average risk for a U.S. investor who invests in foreign currencies.

In addition to DOL, the global FX volatility innovations (ΔVOL_{FX}) factor is employed in the two factor model. Menkhoff et al. (2012a) adopt this two factor model in currency carry trades and show that the price of the volatility factor is negative and the low interest rate currency portfolio has a positive beta to this risk. This finding is important since the low interest rate currency portfolio acts as a hedge, and this is consistent with a risk-based story for a positive return of carry trades. The global FX volatility innovation factor is computed by the following three steps. Let the daily log return of currency j on day d be $r_{j,d} = s_{j,d} - s_{j,d-1}$, where $s_{j,d}$ is the log of the spot exchange rate on day d. First, this study estimates global FX volatility, $\sigma_{FX,d}$, in day d as:

$$\sigma_{FX,d} = \sum_{j=1}^{K_d} \left(\frac{|r_{j,d}|}{K_d} \right) \tag{4.11}$$

where $|r_{j,d}|$ is the absolute value of $r_{j,d}$, and K_d is the number of currencies on day d. Although Menkhoff et al. (2012a) extract the innovation part using monthly data, this chapter's data is at a daily frequency. The second step involves computing the innovation in FX volatility, $\Delta\sigma_{FX,d}$ which is computed as the difference in FX volatility between d and $d - 22$ (assuming the standard 22 trading days in a month).[6] Finally, a factor mimicking portfolio is constructed using these volatility innovations. The volatility innovations are transformed into a traded asset through a mimicking portfolio (e.g., Ang et al., 2006 and Menkhoff et al., 2012a). To construct the mimicking portfolio, this study regresses the volatility factor, $\Delta\sigma_{FX,d}$, onto five carry trade portfolio returns:

$$\Delta\sigma_{FX,d} = a + b'R_d + \epsilon_{i,d} \tag{4.12}$$

where a is a constant, R_d is a return vector of the carry trade portfolios. The factor-mimicking portfolio, $\Delta VOL_{FX,d}$, is obtained using the estimated $\hat{b}$ and the return vector, as $\Delta VOL_{FX,d} = \hat{b}'R_d$.

4.3.3 State Variables

This chapter explores relations between the time variation of conditional alphas and betas, and market state variables. It therefore goes beyond merely identifying that the asset price models parameters are time-varying, this study seeks to identify why alphas and betas fluctuate. This study considers the following state variables that are likely to be related to FX markets:

[6]Since the difference between d and $d - 1$ is too noisy, this study uses this definition.

1. $SHORT$ is the three-month Treasury Bill yield. Ang and Kristensen (2012) show that the conditional beta of the value stock portfolio becomes low when the short term interest rate rises. The short term interest rate contains information about future macroeconomic activities and stock markets (e.g., Fama and Schwert, 1977; Breen et al., 1989; King and Watson, 1996; Ang and Bekaert, 2007). Lustig et al. (2014) propose a theoretical model that links the U.S. short term interest rate with the volatility of the U.S. pricing kernel. The short term rate becomes low in a business cycle trough for precautionary savings.

2 . $TERM$ is the term spread computed as the difference between the 10-year and three-month Treasury Bill yields. Fama and French (1989) demonstrate that the term spread co-moves with business cycles and is related to stock and bond markets (e.g., Ferson and Harvey, 1999; Chordia and Shivakumar, 2002; Petkova, 2006; Maio and Santa-Clara, 2012; Acharya et al., 2013). Furthermore, Ang and Chen (2013) present that the term spread also contains exchange rate market information.

3 . IP is log year-on-year change in the U.S. industrial production index. Ludvigson and Ng (2009) find that the common component of U.S. macroeconomic activities is highly correlated with industrial production growth. Lustig et al. (2014) use the industrial production growth to capture a countercyclical risk premium on expected depreciation of the U.S. dollar.

4. VOL_{FX} is the global FX volatility. This study employs the approach proposed by Menkhoff's et al. (2012a) and estimates global FX volatility, $\sigma_{FX,t}$, in month t using daily volatility, $\sigma_{FX,d}$, as:

$$\sigma_{FX,t} = \frac{1}{T_t} \sum_{d=1}^{T_t} \sigma_{FX,d} \tag{4.13}$$

where T_t is the total number of trading days in month t. The level of volatility is used (eg., Ang and Kristensen, 2012).

5. TED is the TED spread, which is the difference between the three-month Eurodollar LIBOR rate and the three-month Treasury Bill rate. This value reflects banks' funding constraints. Brunnermeier et al. (2009) show that the TED spread predicts future carry trade returns. It is also associated with supply side liquidity of currency markets (see Karnaukh et al., 2015).

6. $DMKT$ denotes the downside global stock market excess return. It is computed using a dummy variable equal to 1 if the world stock market excess return is negative, and zero otherwise. The downside stock market risk is linked to carry trade risk (e.g., Atanasov and Nitschka, 2014; Dobrynskaya, 2014; Lettau et al., 2014). The downside stock market risk is computed as follows:

$$DMKT_t = dummy \times WMKT_t \tag{4.14}$$

where $WMKT_t$ is the global stock market excess return in month t, which is computed by the MSCI world index return (U.S. dollar base). The one month Treasury Bill rate is used as the risk free rate and is subtracted from the world index return.

7. BAS is the global bid-ask spread as in Menkhoff et al. (2012a). This study follows a similar approach to that adapted for VOL_{FX}. The time-varying global FX bid-ask spread measure, BAS_t, in month t is obtained as:

$$BAS_t = \frac{1}{T_t} \sum_{d=1}^{T_t} \sum_{j=1}^{K_d} \left(\frac{\psi_{j,d}}{K_d} \right) \tag{4.15}$$

where $\psi_{j,d}$ is the bid-ask spread measure of the spot exchange rate j at day d.

8. CS is the Corwin and Shultz (2012) liquidity measure of FX markets. This measure focuses on high and low prices in one day and over two days. The daily high price is a buyer-initiated trade, which raises the spread by half, and the daily low price is a seller initiated trade which discounts the spread by half. Karnaukh et al. (2015) find empirical evidence that this measure replicates high-frequency liquidity in FX markets. This study uses overnight adjusted high and low spot exchange rates (see Karnaukh et al. ,2015).

4.4 Empirical Results

4.4.1 Summary Statistics and OLS Estimation

This section begins by presenting summary statistics of currency portfolios and OLS estimation results in Table 4.1. Panel A shows the annualized mean excess returns and standard deviations. The average return of the low interest rate currency portfolio, P1, is -0.71%, and that of the high interest rate currency portfolio, P5, is 4.69%. The average returns increase monotonically from P1 to P5. This pattern is similar when only developed country currencies are used in Panel B.

The fourth and fifth columns in Panel A in Table 4.1 report the OLS coefficient estimates of equation (4.1) where both alphas and betas are constant. The estimated alphas ($\hat{\alpha}$) are annualized by multiplying by 252, as in Ang and Kristensen (2012). All estimated alphas are statistically significant at the 1% level. The result for P1 indicates that the low interest currency portfolio gives a 2.2% lower yield when this study controls for the average effect of investing in foreign currencies. The estimated alphas show a monotonically increasing pattern as reported in the empirical UIP literature. Panel C reports the OLS estimation results of the two factor model that includes the average U.S. dollar, DOL, and the global FX volatility innovations, ΔVOL_{FX}. The estimated alphas are smaller than those of the one factor model and insignificant, except those of P2. This suggests that the combination of DOL and ΔVOL_{FX} successfully captures systematic risk in currency portfolios. The estimated betas of ΔVOL_{FX} monotonically decrease from P1, which has the largest exposure, to P5, which has the smallest exposure. The low interest rate currency portfolio yields a higher return when FX volatility is high because it is less risky. Overall, the two factor model estimated by the time invariant model explains most fluctuations of the portfolio returns.

4.4.2 Long-run Alpha and Beta Estimation

This section now turns to the central set of results in this chapter. Table 4.2 presents the estimate results of the conditional factor model. The second column reports the estimation results of bandwidth obtained by the plug-in method. Following Ang and Kristensen (2012), the bandwidths are transformed to monthly equivalent units in the third column of Table 4.2.[7] If conditional estimators have high time variations, this estimated bandwidth provides a tighter window. For all country results, low interest rate currency portfolios such as P1 and P2, have longer windows in Panel A. Overall, the estimated window sizes are somewhat longer than the 36 months employed in rolling regressions by Lustig et al. (2011). This implies that the changes in betas are slower compared with those assumed by the conventional method. It may be useful to check both results estimated by the window sizes of 36 and 60 months when we use the conventional rolling window approach.

[7]These values are obtained as the fractions $\times 320 \times 1.96/0.975$.

TABLE 4.1: Summary Statistics of Currency Portfolios and OLS Estimates

Portfolio	Mean	S.D.	$\hat{\alpha}$	$\hat{\beta}_{DOL}$	$\hat{\beta}_{\Delta VOLFX}$
Panel A: All countries and one factor model					
P1	-0.71	0.13	-2.114***	1.022***	
			(0.061)	(0.047)	
P2	-0.01	0.11	-1.226***	0.880***	
			(0.045)	(0.030)	
P3	0.94	0.11	-0.388***	0.945***	
			(0.048)	(0.036)	
P4	2.13	0.13	0.610***	1.073***	
			(0.079)	(0.058)	
P5	4.69	0.17	3.118***	1.080***	
			(0.097)	(0.053)	
Panel B: Developed countries and one factor model					
P1	-1.08	0.17	-1.496***	1.094***	
			(0.062)	(0.055)	
P2	-0.31	0.12	-0.648***	0.859***	
			(0.030)	(0.045)	
P3	0.34	0.13	-0.065***	0.991***	
			(0.026)	(0.046)	
P4	0.92	0.15	0.490***	1.043***	
			(0.039)	(0.073)	
P5	2.16	0.14	1.718***	1.012***	
			(0.043)	(0.054)	
Panel C: All countries and two factor model					
P1			0.145	1.060***	6.130***
			(0.106)	(0.015)	(0.310)
P2			-0.297**	0.896***	2.520***
			(0.151)	(0.034)	(0.461)
P3			-0.049	0.951***	0.919***
			(0.115)	(0.039)	(0.351)
P4			0.043	1.063***	-1.538**
			(0.309)	(0.055)	(0.701)
P5			0.159	1.031***	-8.032***
			(0.367)	(0.042)	(1.010)
Panel D: Developed countries and two factor model					
P1			-0.068	0.996***	4.196***
			(0.111)	(0.059)	(0.290)
P2			-0.471***	0.847***	0.519***
			(0.071)	(0.042)	(0.193)
P3			0.311***	0.965***	1.103***
			(0.059)	(0.040)	(0.136)
P4			-0.420	1.106***	-2.674***
			(0.341)	(0.080)	(0.976)
P5			0.648***	1.086***	-3.144***
			(0.236)	(0.059)	(0.676)

Notes: This table presents the summary statistics of currency portfolios and OLS estimates. Annualized mean returns and standard deviations (S.D.) of currency portfolios are computed by multiplying daily estimate by 252 and $\sqrt{252}$. $\hat{\alpha}$, $\hat{\beta}_{DOL}$, and $\hat{\beta}_{\Delta VOLFX}$ are obtained by regressing each currency return on a constant, the dollar (DOL) and the global FX volatility innovations (ΔVOL_{FX}). The standard errors are reported in parentheses and obtained by the Newey and West (1987) procedure with optimal lag selection according to Andrews (1991). Asterisk *,**, and *** indicate significance at the 10%, 5% and 1% levels, respectively.

The fourth and fifth columns of Panel A in Table 4.2 report the long-run conditional alphas and betas. The long-run bandwidth in equation (4.6) is used for estimation. All alphas are highly significant and increase monotonically from P1 to P5. The long-run alpha of P1 is -1.9, and this is slightly higher than that of the OLS result, -2.1. The long-run conditional betas on DOL are also highly significant, and the magnitudes are around one. Time variations of betas generate smaller standard errors than those of the constant OLS model. The same estimations are conducted using developed country portfolios in Panel B. Developed country results show similar patterns to those exhibited by the all country results. Panel C presents the results of the two factor model. Importantly, all estimated alphas become statistically significant at the 1% level, except P4. This implies that there is risk that is not captured by these two factors. The contrasting results between Tables 4.1 and 4.2 imply that this study needs to be cautious to conclude the two factor model captures all systematic risk on currency portfolios. The estimated betas on ΔVOL_{FX} exhibit the same monotonically decreasing pattern reported in Table 4.1.[8] This indicates that the high interest rate currency portfolios are more risky since they are more exposed to the volatility risk.

Next, this section formally tests whether or not the conditional alphas and betas are constant. Table 4.3 presents the test statistics that are computed by equation (4.9). Panel A shows that the null hypotheses of constant alphas and betas are rejected at the 1% level, since the F values are greater than the 99%

[8]This study estimates the other two factor model which has the DOL and HML_{FX} proposed by Lustig et al. (2011) in the Appendix.

TABLE 4.2: Long-run Alphas and Betas

Portfolio	Fraction	Months	$\hat{\alpha}_{LR}$	$\hat{\beta}_{DOL}$	$\hat{\beta}_{\Delta VOLFX}$
Panel A: All countries and one factor model					
P1	0.085	54.9	-1.909***	0.967***	
			(0.023)	(0.009)	
P2	0.095	61.1	-1.198***	0.971***	
			(0.014)	(0.007)	
P3	0.077	49.7	-0.500***	0.986***	
			(0.014)	(0.007)	
P4	0.065	41.5	0.549***	0.985***	
			(0.025)	(0.010)	
P5	0.082	52.8	3.069***	1.085***	
			(0.024)	(0.012)	
Panel B: Developed countries and one factor model					
P1	0.097	62.6	-1.414***	1.011***	
			(0.018)	(0.013)	
P2	0.055	35.6	-0.493***	1.011***	
			(0.009)	(0.008)	
P3	0.079	50.8	-0.015*	1.073***	
			(0.009)	(0.007)	
P4	0.069	44.5	0.280***	0.948***	
			(0.013)	(0.009)	
P5	0.108	69.7	1.645***	0.9624***	
			(0.012)	(0.009)	
Panel C: All countries and two factor model					
P1	0.069	44.1	0.266***	1.007***	6.492***
			(0.012)	(0.003)	(0.031)
P2	0.083	53.3	-0.462***	1.015***	2.053***
			(0.024)	(0.007)	(0.061)
P3	0.071	45.9	-0.630***	0.993***	-0.736***
			(0.027)	(0.007)	(0.066)
P4	0.079	50.5	0.031	0.988***	-1.769**
			(0.040)	(0.010)	(0.088)
P5	0.059	38.0	0.831***	0.991***	-5.971***
			(0.035)	(0.009)	(0.082)
Panel E: Developed countries and two factor model					
P1	0.103	66.3	-0.420***	0.893***	3.470***
			(0.027)	(0.011)	(0.061)
P2	0.087	56.0	-0.483***	1.012***	-0.148***
			(0.019)	(0.008)	(0.046)
P3	0.145	93.4	0.538***	0.985***	1.653***
			(0.017)	(0.007)	(0.037)
P4	0.124	79.7	-0.282***	1.021***	-1.781***
			(0.024)	(0.008)	(0.042)
P5	0.108	69.6	0.654***	1.084***	-3.220***
			(0.018)	(0.006)	(0.034)

Notes: This table presents the conditional bandwidths, long-run alphas, and betas on the dollar (DOL) and the global FX volatility innovations (ΔVOL_{FX}). The conditional bandwidth is reported in fractions of the entire sample and obtained as in Kristensen (2012). They are transformed to monthly equivalent units by multiplying $320 \times 1.96/0.975$, where there are 320 months in the sample. The long-run alpha and betas are obtained by equation (4.4) and the standard errors are reported in parentheses and obtained by equation (4.5). The long-run alphas are annualized to multiply 252. Asterisk *,**, and *** indicate significance at the 10%, 5% and 1% levels, respectively.

critical values reported in the last column. Accordingly, the long-run conditional alphas and betas vary over time. The time variation of the long-run estimators are related to the time-varying UIP deviations of Bansal (1997) and Baillie and Kim (2015). This study goes beyond these studies, since this study considers the portfolio approach and evidences that time-varying UIP deviations hold in currency portfolios. Panels B, C, and D indicate that developed country portfolios and the two factor model also have time-varying conditional alphas and betas.

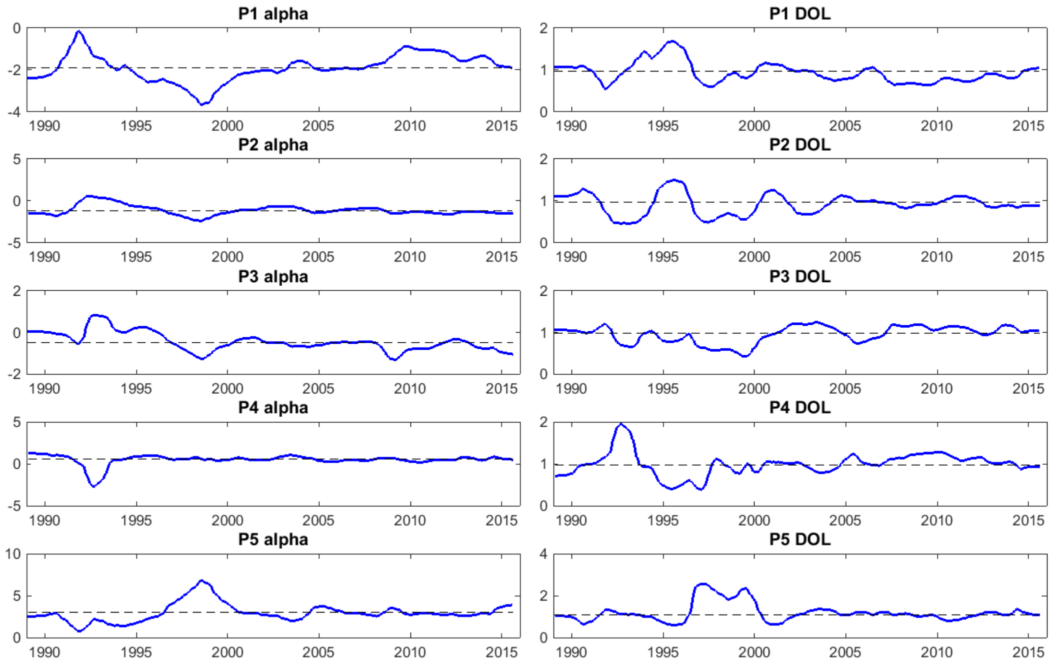
TABLE 4.3: Tests of Constant Alphas and Betas

	F-statistics			Critical Value	
Portfolio	α_{LR}	β_{DOL}	$\beta_{\Delta VOLFX}$	95%	99%
Panel A: All countries and one factor model					
P1	290***	1480***		71	76
P2	6503***	9963***		64	69
P3	2864***	6360***		78	83
P4	2304***	4985***		91	97
P5	6687***	2263***		73	79
Panel B: Developed countries and one factor model					
P1	271***	228***		63	68
P2	1180***	4210***		106	112
P3	1506***	6340***		76	81
P4	2650***	5319***		86	92
P5	1636***	1047***		57	62
Panel C: All countries and two factor model					
P1	3925***	4712***	9863***	86	92
P2	3930***	11638***	4034***	72	78
P3	3427***	7394***	3523***	84	89
P4	5981***	7738***	3667***	76	81
P5	5028***	2000***	17557***	99	106
Panel D: Developed countries and two factor model					
P1	1010***	2107***	730***	60	64
P2	1004***	3133***	788***	69	75
P3	921***	575***	307***	44	48
P4	1166***	780***	670***	50	55
P5	894***	60**	208***	57	62

Notes: This table presents the test of constancy of the alphas and betas on the dollar (DOL) and the global FX volatility innovations (ΔVOL_{FX}). F statistic is computed by equation (4.9) and 95% and 99% critical values are reported. Asterisk *,**, and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Figure 4.1, which plots the conditional alphas and betas on DOL, illustrate the time variation of these parameters. We can observe the alphas and betas have the time variations. Figure 4.2 plots conditional alphas and betas estimated by the two factor model. Interestingly, the shapes of the alphas in Figure 4.2 are different from those in Figure 4.1. This suggests the importance of controlling for ΔVOL_{FX}.

FIGURE 4.1: Conditional alphas and betas of one factor model

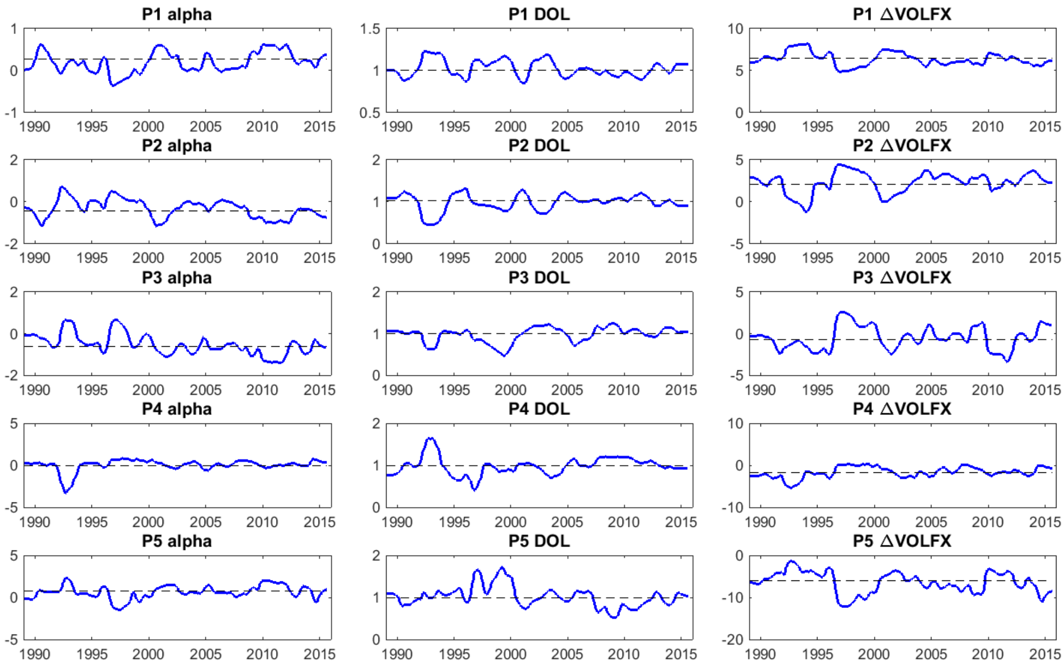


Notes: This figure provides plots of the estimated conditional short-run (thick line) and the average of long-run (dash line) alphas and betas of all country portfolios. The one factor model includes the dollar (DOL).

4.4.3 State Variables and One Factor Model

Having established that conditional alphas and betas vary over time, this section explores the main possible drivers of theses time variations. Following Ang and Kristensen (2012), this study picks up the end-of-month values of the alphas and betas and regresses them on the state variables described in

FIGURE 4.2: Conditional alphas and betas of two factor model



Notes: This figure provides plots of the estimated conditional short-run (thick line) and the average of long-run (dash line) alphas and betas of all country portfolios. The two factor model includes the dollar (DOL) and the global FX volatility innovations (ΔVOL_{FX})

the previous section.[9] Table 4.4 reports the results, and this study focuses on P1 and P5. Panel A presents results showing that the short term rate, term spread, and FX market volatility, are significant at the 1% level. In particular, the R^2 of $SHORT$ and $TERM$ are higher than those of Ang and Kristensen (2012) for the stock market. Importantly, columns (1) to (4) show that the alpha of P1 increases in bad states, because P1 includes less risky currencies. For instance, the low short term rate is related to a business cycle trough as reported by Fama (1990). The negative coefficient of $SHORT$, -0.19, indicates that as short interest rate rises the alpha of P1 declines. VOL_{FX} increases when FX markets are more volatile, and the alpha of P1 increases. All variables are included together in column (9), and the coefficient of $SHORT$ and VOL_{FX} remain statistically significant at least at the 5% level. Further, and for robustness, this study also employs two model reduction techniques: the general to specific approach and the least angle regressions (LAR) approach. The results are in the Appendix to this chapter. The basic idea of the general to specific approach is to systematically delete insignificant variables.[10] The LAR approach proposed by Efron et al. (2004) allows for the reduction of the computation time. Using these approaches, the main results remain qualitatively the same.

Panel B in Table 4.4 provides the results of P5. These show a less clear pattern than the results of P1, since most results provide smaller R^2 than those of P1, except the term spread in column (2). The sign of $TERM$ in P5 is opposite to that for P1. The alpha in P5 becomes low in bad economic states, since the term spread is high in a business cycle trough, as shown by Fama and French (1989). In summary, Table 4 presents evidence that the alpha of the low interest rate currency portfolio increases in bad economic states, and that of the high interest rate currency portfolio decreases. This is particularly clear in the

[9]This study uses the sample period from February 1991 to December 2013 due to data availability.

[10]See for example Krolzig and Hendry (2001).

results of the low interest rate currency portfolio. These findings are consistent with the risk-based explanation suggested by Lustig and Verdelhan (2007) who use the consumption CAPM in the cross-sectional context. The analysis adopting the different factor model presents the similar findings in the time series context.

The fluctuations of the conditional betas show a different relation to the fluctuations of the conditional alphas. Panel A in Table 4.5 presents results showing that $SHORT$, $TERM$, VOL_{FX}, and CS are statistically significant at the 1% level. The signs of these state variables are opposite to those of Table 4.4. This indicates that the beta of the low interest rate currency portfolio decreases in bad states. Taken together, the results in Tables 4.4 and 4.5 show that the low interest rate currency portfolio has a higher alpha and a smaller factor exposure to DOL in bad economic states. Panel B provides the results of P5. Coefficients of $SHORT$ and VOL_{FX} in P5 have the same signs as those in P1. This suggests that the betas of P1 and P5 move in the same direction. Moreover, they imply that there is heterogeneity in factor exposure between the low and high interest rate currency portfolios, since CS is statistically significant at the 1% level in P1 but not in P5. Overall, we observe the alphas estimated by the one factor model are linked to economic states. This study proceeds by including the FX volatility innovations in the next section.

4.4.4 State Variables and Two Factor Model

Table 4.6 presents the alpha results of the two factor model. It shows that $SHORT$ and VOL_{FX} are the main drivers of the fluctuation of the alpha in P1. This result is consistent with that of the one factor model in Table 4.4. However, the alpha in P5 is positively related to economic states in Panel B of Table 4.6, and this contrasts with the result of the one factor model. Further,

TABLE 4.4: Explaining Conditional Alphas Estimated by One Factor Model

Panel A: Portfolio 1									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$SHORT$	-0.19***								-0.10**
	(0.05)								(0.05)
$TERM$		0.37***							0.16*
		(0.12)							(0.10)
IP			-0.07**						-0.03
			(0.03)						(0.02)
VOL_{FX}				1.43***					2.46***
				(0.35)					(0.73)
TED					-0.43				-0.11
					(0.42)				(0.15)
$DMKT$						-0.01			0.00
						(0.01)			(0.01)
BAS							-1.13		-0.15
							(5.39)		(3.27)
CS								0.11	-0.68**
								(0.22)	(0.28)
$adjR^2$	0.32	0.40	0.17	0.10	0.05	0.00	0.00	0.00	0.55
Panel B: Portfolio 5									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$SHORT$	0.10								-0.11
	(0.08)								(0.09)
$TERM$		-0.49**							-0.49***
		(0.24)							(0.15)
IP			0.05						0.04
			(0.06)						(0.03)
VOL_{FX}				-0.03					-4.78***
				(0.48)					(0.95)
TED					0.88				0.11
					(0.62)				(0.34)
$DMKT$						-0.01			0.02
						(0.02)			(0.02)
BAS							6.34		7.11
							(9.03)		(4.85)
CS								0.67*	1.76***
								(0.35)	(0.32)
$adjR^2$	0.03	0.24	0.03	0.00	0.07	0.00	0.04	0.10	0.55

Notes: This table shows the results of monthly conditional alphas of P1 and P5 are regressed on market state variables. These alphas are estimated by the one factor model which has the dollar (DOL). The portfolios are constructed by all country currencies. The monthly data is obtained as the end of the month daily conditional alphas. $SHORT$ is the three month T-Bill yield, $TERM$ is the difference between 10 year and three month T-Bill yields, IP is the industrial production growth, VOL_{FX} is the global FX volatility, TED is the TED spread, $DMKT$ is the downside stock market excess return, BAS is the global FX bid-ask-spreads, and CS is the Corwin and Schultz liquidity measure. The standard errors are reported in parentheses and obtained by the Newey and West (1987) procedure with optimal lag selection according to Andrews (1991). Asterisk *,**, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

TABLE 4.5: Explaining Conditional Betas on DOL Estimated by One Factor Model

Panel A: Portfolio 1	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$SHORT$	0.05***								0.09***
	(0.01)								(0.03)
$TERM$		-0.04***							0.04
		(0.01)							(0.04)
IP			0.01*						0.00
			(0.01)						(0.01)
VOL_{FX}				-0.45***					0.31
				(0.13)					(0.20)
TED					-0.10*				-0.17***
					(0.05)				(0.07)
$DMKT$						0.01			0.00
						(0.01)			(0.01)
BAS							-1.57		-2.73**
							(1.13)		(1.12)
CS								-0.16***	-0.03
								(0.05)	(0.08)
$adjR^2$	0.16	0.03	0.05	0.07	0.02	0.00	0.05	0.13	0.34
Panel B: Portfolio 5	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$SHORT$	0.05**								-0.02
	(0.02)								(0.05)
$TERM$		-0.08							-0.02
		(0.06)							(0.06)
IP			0.03						0.03
			(0.03)						(0.02)
VOL_{FX}				-0.56**					-1.39***
				(0.28)					(0.33)
TED					0.19				0.27
					(0.22)				(0.18)
$DMKT$						0.01			0.01
						(0.01)			(0.01)
BAS							3.32*		4.00***
							(2.02)		(1.53)
CS								-0.01	0.24**
								(0.10)	(0.11)
$adjR^2$	0.06	0.04	0.09	0.03	0.04	0.00	0.07	0.00	0.26

Notes: This table shows the results of monthly conditional betas on DOL_{FX} of P1 and P5 are regressed on market state variables. These betas are estimated by the one factor model which has the dollar (DOL). The portfolios are constructed by all country currencies. The monthly data is obtained as the end of the month daily conditional betas. $SHORT$ is the three month T-Bill yield, $TERM$ is the difference between 10 year and three month T-Bill yields, IP is the industrial production growth, VOL_{FX} is the global FX volatility, TED is the TED spread, $DMKT$ is the downside stock market excess return, BAS is the global FX bid-ask-spreads, and CS is the Corwin and Schultz liquidity measure. The standard errors are reported in parentheses and obtained by the Newey and West (1987) procedure with optimal lag selection according to Andrews (1991). Asterisk *,**, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

once ΔVOL_{FX} is controlled for, the alpha of P5 increases in bad states. This implies that the procyclical pattern of the alpha in P5 is explained by the FX market risk.

Panel A in Table 4.7 presents the results of beta on DOL in P1. Although some variables are statistically significant, most R^2 are small, and these reflect weak relations between factor beta fluctuations and state variables. Panel B displays the procyclical relation between the beta and economic states in P5, as was done in Table 4.5. The R^2 of $SHORT$ and IP are higher than those of the one factor model. Furthermore, the FX market liquidity, CS, is linked to the variation of the beta in P5. In summary, the state variables are related to fluctuations of betas on DOL in the risky portfolio, after controlling for the effect of FX market volatility.

Finally, this study focuses on the betas on ΔVOL_{FX} in Table 4.8. The FX volatility VOL_{FX} is excluded from the regressors, since the betas are directly linked to FX market volatility. The tabulated values in Panels A and B indicate that TED is strongly related to the fluctuation of the betas in P1 and P5. These show that when market liquidity dries up, the betas decrease in P1 and P5. $TERM$ is also an important driver for P5 in Panel B. These two variables remain statistically significant in column (8) when all variables are included simultaneously. Further, this result is robust to the use of model reduction approaches (see the Appendix). Thus, overall, the conditional betas on the dollar and the FX volatility innovations are driven by different mechanisms. Accordingly, it seems that the betas on DOL are driven by basic macroeconomic variables, such as the short interest rate and IP growth, but the betas on ΔVOL_{FX} are associated with interest rate spread variables.

TABLE 4.6: Explaining Conditional Alphas Estimated by Two Factor Model

Panel A: Portfolio 1									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$SHORT$	-0.02**								-0.01
	(0.01)								(0.01)
$TERM$		0.02							-0.01
		(0.02)							(0.01)
IP			-0.01*						0.00
			(0.00)						(0.00)
VOL_{FX}				0.20***					0.15
				(0.06)					(0.10)
TED					-0.04				-0.08***
					(0.03)				(0.02)
$DMKT$						0.00			0.00
						(0.00)			(0.00)
BAS							-0.42		-0.35
							(0.35)		(0.30)
CS								0.05**	0.01
								(0.02)	(0.04)
$adjR^2$	0.22	0.05	0.12	0.11	0.02	0.00	0.02	0.08	0.33
Panel B: Portfolio 5									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$SHORT$	-0.07***								-0.04
	(0.02)								(0.03)
$TERM$		0.12***							0.01
		(0.04)							(0.04)
IP			-0.02						-0.01
			(0.02)						(0.01)
VOL_{FX}				0.58**					0.74**
				(0.25)					(0.31)
TED					-0.26*				-0.27***
					(0.13)				(0.06)
$DMKT$						0.00			-0.01
						(0.00)			(0.00)
BAS							-0.03		0.44
							(1.89)		(1.27)
CS								0.09	-0.10
								(0.07)	(0.14)
$adjR^2$	0.24	0.20	0.09	0.08	0.09	0.00	0.00	0.02	0.35

Notes: This table shows the results of monthly conditional alphas of P1 and P5 are regressed on market state variables. These alphas are estimated by the two factor model which has the dollar (DOL) and the global FX volatility innovations (ΔVOL_{FX}). The portfolios are constructed by all country currencies. The monthly data is obtained as the end of the month daily conditional alphas. $SHORT$ is the three month T-Bill yield, $TERM$ is the difference between 10 year and three month T-Bill yields, IP is the industrial production growth, VOL_{FX} is the global FX volatility, TED is the TED spread, $DMKT$ is the downside stock market excess return, BAS is the global FX bid-ask-spreads, and CS is the Corwin and Schultz liquidity measure. The standard errors are reported in parentheses and obtained by the Newey and West (1987) procedure with optimal lag selection according to Andrews (1991). Asterisk *,**, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

TABLE 4.7: Explaining Conditional Betas on DOL Estimated by Two Factor Model

Panel A: Portfolio 1									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$SHORT$	0.00								-0.01*
	(0.01)								(0.01)
$TERM$		0.02							0.01
		(0.02)							(0.01)
IP			0.01***						0.01**
			(0.00)						(0.00)
VOL_{FX}				-0.14**					-0.14**
				(0.06)					(0.07)
TED					-0.04				0.03
					(0.03)				(0.02)
$DMKT$						0.00			0.00
						(0.00)			(0.00)
BAS							1.17***		1.63***
							(0.25)		(0.29)
CS								-0.04**	-0.05**
								(0.02)	(0.02)
$adjR^2$	0.00	0.03	0.05	0.04	0.01	0.00	0.19	0.04	0.40
Panel B: Portfolio 5									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$SHORT$	0.06***								0.03
	(0.02)								(0.02)
$TERM$		-0.08**							-0.02
		(0.03)							(0.03)
IP			0.03***						0.02**
			(0.01)						(0.01)
VOL_{FX}				-0.71***					-0.33*
				(0.13)					(0.20)
TED					-0.05				-0.04
					(0.17)				(0.11)
$DMKT$						0.01*			0.01*
						(0.00)			(0.00)
BAS							1.17		1.50
							(1.05)		(0.94)
CS								-0.16**	0.02
								(0.06)	(0.06)
$adjR^2$	0.24	0.12	0.28	0.18	0.00	0.02	0.02	0.11	0.43

Notes: This table shows the results of monthly conditional betas on DOL of P1 and P5 are regressed on market state variables. These betas are estimated by the two factor model which has the dollar (DOL) and the global FX volatility innovations (ΔVOL_{FX}). The portfolios are constructed by all country currencies. The monthly data is obtained as the end of the month daily conditional betas. $SHORT$ is the three month T-Bill yield, $TERM$ is the difference between 10 year and three month T-Bill yields, IP is the industrial production growth, VOL_{FX} is the global FX volatility, TED is the TED spread, $DMKT$ is the downside stock market excess return, BAS is the global FX bid-ask-spreads, and CS is the Corwin and Schultz liquidity measure. The standard errors are reported in parentheses and obtained by the Newey and West (1987) procedure with optimal lag selection according to Andrews (1991). Asterisk *,**, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

TABLE 4.8: Explaining Conditional Betas on ΔVOL_{FX} Estimated by Two Factor Model

Panel A: Portfolio 1								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$SHORT$	-0.02							0.09
	(0.04)							(0.06)
$TERM$		0.24*						0.30***
		(0.14)						(0.10)
IP			-0.01					-0.01
			(0.05)					(0.05)
TED				-0.58**				-0.43
				(0.26)				(0.27)
$DMKT$					-0.01			-0.05**
					(0.00)			(0.02)
BAS						2.17		1.42
						(4.20)		(2.86)
CS							-0.25	-0.21*
							(0.16)	(0.12)
$adjR^2$	0.00	0.12	0.00	0.07	0.00	0.01	0.03	0.21

Panel B: Portfolio 5								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$SHORT$	-0.23							0.30
	(0.15)							(0.20)
$TERM$		1.03***						1.17***
		(0.35)						(0.31)
IP			-0.03					-0.03
			(0.18)					(0.15)
TED				-2.88***				-2.14***
				(0.79)				(0.70)
$DMKT$					-0.02			-0.09**
					(0.04)			(0.04)
BAS						-0.84		-3.45
						(17.09)		(9.15)
CS							-0.99*	-0.42
							(0.55)	(0.52)
$adjR^2$	0.03	0.22	0.00	0.17	0.00	0.00	0.04	0.34

Notes: This table shows the results of monthly conditional betas on ΔVOL_{FX} of P1 and P5 are regressed on market state variables. These betas are estimated by the two factor model which has the dollar (DOL) and the global FX volatility innovations (ΔVOL_{FX}). The portfolios are constructed by all country currencies. The monthly data is obtained as the end of the month daily conditional betas. $SHORT$ is the three month T-Bill yield, $TERM$ is the difference between 10 year and three month T-Bill yields, IP is the industrial production growth, VOL_{FX} is the global FX volatility, TED is the TED spread, $DMKT$ is the downside stock market excess return, BAS is the global FX bid-ask-spreads, and CS is the Corwin and Schultz liquidity measure. The standard errors are reported in parentheses and obtained by the Newey and West (1987) procedure with optimal lag selection according to Andrews (1991). Asterisk *,**, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

4.5 Conclusion

Time variation of alphas and factor betas of portfolio returns is widely explored in the asset pricing literature. Conditional factor models with have state dependent betas have been successfully applied in stock market studies. For instance, Lewellen and Negal (2006) propose a new method to estimate a conditional factor model using high frequency data, and Ang and Kristensen (2012) extend it through nonparametric methods. This chapter is the first empirical research to apply a nonparametric conditional factor model to investigate currency carry trades. The time-varying behaviour of UIP has already been explored by Bansal (1997) and Baillie and Kilic (2006), but, to my knowledge, the time-varying alphas and betas of currency portfolios have not hitherto been considered.

The empirical findings show that the conditional alphas and betas on the dollar risk (DOL) of Lustig et al. (2011) and the FX volatility innovations (ΔVOL_{FX}) of Menkhoff et al. (2012a) vary over time. The conditional alphas are statistically significant, and this suggests the existence of profitability not captured by the well known systematic factors. Further, this chapter shows that the conditional alphas are related to economic states. The low (high) interest rate currency portfolio has a higher (lower) alpha in bad economic states. This finding is consistent with the risk-based explanation of currency carry trades proposed by Lustig and Verdelhan (2007). This chapter finds that the relation between the alpha and economic states disappears in the high interest rate portfolio when FX market volatility innovations are controlled for. This implies that a certain amount of premium in the high interest rate currency portfolio comes from FX market risk. This study also presents evidence that the conditional betas on DOL decrease in bad economic states, and are negatively correlated to FX market liquidity. The conditional betas on ΔVOL_{FX} are linked to the TED and the term spreads. These findings imply that the fluctuations of betas on DOL and ΔVOL_{FX} are driven by different mechanisms.

Chapter 5

The Time-varying Risk Prices of Currency Carry Trades

5.1 Introduction

As mentioned in Chapters 2 to 4, currency carry trades are implemented by borrowing in low interest rate currencies and investing in high interest rate currencies. Asset pricing theory suggests that positive carry returns are compensations for risk. An expanding body of literature tests competing theories in a quest to identify the risk factors that are relevant to carry returns. This literature explores expected returns on risk factors, and these factors are associated with positive or negative factor betas and risk prices as rewards for bearing the risk of theses factors. Using returns on currency portfolios, rather than individual currencies, recent studies have sought to identify both the factor betas and risk prices for carry returns. For example, Lustig and Verdelhan (2007) employ the consumption CAPM, while Burnside et al. (2011) investigate whether the Fama and French (1993) three factor model explains carry returns. Currency carry trade specific factors were also introduced by Lustig et al. (2011) and Menkhoff et al. (2012a). In particular, Lustig et al. (2011) propose a level and a slope factor model, known as their dollar (DOL) and carry

(HML_{FX}) factors, and the latter can price cross-sectional currency portfolios, although the dollar does less well. Two questions naturally arise: how do we interpret the level and slope factors? Are factor betas and/or risk prices constant or time varying when modelling carry return risks? One possible solution to factor interpretation and time variation is to introduce forecast variables as proxies to capture changes in economic states and build a conditional factor model. Such a model would provide a mechanism by which risk prices can change over time through changes in the forecast variables.[1]

Studies in the carry trade literature typically use unconditional models to estimate carry factor betas and risk prices, although there are good reasons to believe that currency risk factors may have time-varying betas and/or risk prices. The broad asset pricing literature mainly focuses on time-varying betas[2] but not time varying risk prices. Factor betas, indeed, are key elements for portfolio risk management, and investors are likely to adjust betas to optimise their portfolio risk level. However, Ferson and Harvey (1991), Evans (1994), and Adrian et al. (2015), amongst others, show that time-varying risk prices play an important role in expected returns for stock and bond markets. It is plausible to assume that time variation of risk prices is substantial since the representative investor may have time-varying risk aversion in carry trades. Nagel (2013) states that investors are myopic and maximize utility period by period, hence accounting for time-varying risk-aversion is required. Given currency carry trades have unwinding risk as pointed out by Brunnermeier et al. (2009), it is reasonable to expect the risk-aversion changes after a market crash. Another reason why risk aversion may vary is due to habits. Verdelhan

[1]These forecast variables are not related to forecasting or predictability. They work as state variables to determine time variation of risk prices. However the world of "state variables" have a wider concept in Adrian et al. (2015), see also equation (5.4). To avoid confusion, this chapter calls forecast variables.

[2]Jagannathan and Wang (1996), Cochrane (1996), Ferson and Harvey (1999), and Lettau and Ludvigson (2001) propose conditional factor models in the stock market and allow time-varying betas to reflect changes in economic states.

(2010) proposes a habit model that explains violations of the Uncovered Interest rate Parity (UIP) condition, which is the key mechanism to create positive carry returns.

It is therefore reasonable to expect that time variation is important for the FX market.[3] This chapter would expect portfolio re-adjustments after major economic events. Conditional factor models are more appropriate to managed funds when investors change their positions in response to carry predictability.[4] This predictability reflects time-varying expected returns since investors adjust required returns based on changes in economic states captured by forecast variables. Expected returns are represented by factor betas and risk prices in standard linear factor models. Thus, the time-varying expected returns require time-varying betas and/or risk prices. Christiansen et al. (2011) and Lustig et al. (2011) were early contributions to conditional carry models. Although time-varying betas for carry trades are investigated by Christiansen et al. (2011), time-varying risk prices are not. Lustig et al. (2011) uses rolling regressions to estimate conditional carry models,[5] and although some empirical results are promising, there is no interpretation of the time variation and the conditional results do not fully account for transaction costs. Transaction costs obviously matter to managed funds as they are linked to the frequency of trading dictated by portfolios adjustments. Atanasov and Nitschka (2014), Dobrynskaya (2014), and Lettau et al. (2014) also emphasise conditional carry factor models when estimating time-varying betas, but they do not investigate

[3]The relationship between exchange rates and macro fundamentals is also unstable, consistent with the scape goat theory by Bacchetta and Wincoop (2013). Sarno and Valente (2009), Rossi (2013) and Byrne et al. (2016) among others conduct empirical analysis for exchange rate prediction with time-varying parameters.

[4]Ferson and Harvey (1991) and Ferson and Schadt (1996) emphasise the importance of conditional models for managed investment funds when stock and bond returns are predictable. Studies that suggest carry returns are predictable include Bakshi and Panayotov (2013), Cenedese et al. (2014), and Lu and Jacobsen (2016).

[5]Time-varying risk prices are traditionally explored by rolling regressions as in Ferson and Harvey (1991).

time-varying risk prices.

This chapter extends the carry trade literature on two fronts. First, this chapter's major innovation to the carry trade literature is the modelling of time variation in both factor betas and risk prices. Several recent studies distinguish between up-side and down-side risk prices but do not investigate time variation in risk prices (Atanasov and Nitschka, 2014; Dobrynskaya, 2014; Lettau et al., 2014). This chapter allows for continuous change in risk prices as it explores how they vary over time based on economic states. To this end, this chapter employs econometric methods from Adrian et al. (2015). These methods have successfully been applied to identify time-varying risk prices and factor betas for stock and bond markets. In contrast to rolling regression methods, Adrian et al. (2015) propose a more general approach that incorporates forecast variables with risk factors. The main advantage of this approach relative to the traditional conditional factor model is that it allows for time variation in both risk prices and factor betas. Further, the betas in the model, which are estimated by the non-parametric method of Ang and Kristensen (2012), also fluctuate over time. Non-parametric models are more robust to misspecification, because parametric models tend to overestimate time variations of betas, as pointed out by Ghysels (1998). Factor betas estimated by standard conditional models may be volatile and do not contribute to small pricing errors, while non-parametric models allow smooth changes in betas to improve pricing errors.

This chapter's cross-sectional risk factors are based on Lustig et al. (2011) and Menkhoff et al. (2012a), but the model also includes forecast factors. They allow us to interpret the main drivers of time variation in risk factors. This point is important since Lustig et al.'s (2011) level and slope factors are derived by a data driven approach, and hence interpretation of these factors is an interesting question.

The second contribution of this chapter is to extend the cross-sectional and forecast literature of carry trades. Forecast variables are widely employed in stock and bond market research (e.g. Ferson and Harvey, 1991, 1999). This study employs several forecast factors that include FX market volatility, a commodity price return, and market liquidity. Bakshi and Panayotov (2013) and Cenedese et al. (2014) argue that FX market volatility is related to future carry trade returns. FX market volatility represents uncertainty in FX markets and uncertainty induces unwinding of carry trades. Commodity prices are relevant to carry trades prediction as suggested by Bakshi and Panayotov (2013), because some high interest rate currencies such as the Australian and the New Zealand dollar are commodity exporting currencies. Ready et al. (2016) propose that commodity exporting countries tend to have higher interest rates because they are more robust to consumption shocks. Moreover, Brunnermeier et al. (2009) indicate that market liquidity, measured by the TED spread, is associated with carry trade returns, since lack of market liquidity causes unwinding of carry trades. In this chapter, this study connects these forecast factors to cross-sectional risk factors.

To preview the results in this chapter, this chapter finds significant time variation in the risk price of the carry factor (HML_{FX}) and uncertainty in FX markets creates time variation in the risk price of this factor. Time variation of the dollar and the carry risk prices contribute to smaller pricing errors for the asset pricing model, while time variation of factor betas do not. The weak contribution of the time-varying betas implies that change in the factor betas is slow but investors may overreact to shocks in economic states. The importance of time-varying risk prices suggests that predictability is more related to time variation in the risk prices. The commodity price and the market liquidity variables cause a decline in the risk price on the carry factor during the crisis.

This result reveals that several forecast variables acted as the driving force behind negative returns when disaster struck.[6] This chapter also finds the dollar factor is linked to market liquidity, which is plausible since investors would demand safe assets, such as the U.S. dollar, when market liquidity dries up (flight to safety).

The rest of the chapter is organized as follows: Section 5.2 lays out the econometrics, Section 5.3 describes the data, Section 5.4 presents the empirical results, Section 5.5 presents robustness analyses and Section 5.6 concludes.

5.2 Estimation Methodology

This section sets out the empirical methods. To account for the role of time-varying factor betas and/or risk prices for carry returns, this study adopts Adrian et al.'s (2015) models. This approach is sufficiently flexible to allow for the following two combinations: constant betas but time-varying risk prices, and time-varying betas and risk prices. These distinctive combinations are important, as the results will show below.

5.2.1 Constant Betas and Time-varying Risk Prices

An expected excess return on currency portfolio i, $E[R_i]$, is represented as risk prices lambda, λ, multiplied by factor betas, β_i, using a standard factor pricing model:

$$E[R_i] = \lambda' \beta_i. \tag{5.1}$$

[6]Empirical evidence also indicates that disaster risk plays an important role for carry trade returns. See, Brunnermeier et al., (2009), Burnside et al. (2011), Farhi et al. (2013), Jurek (2014), and Farhi and Gabaix (2016).

The popular Fama and MacBeth (1973) two-step approach is used to obtain factor betas and risk prices. Factor betas are obtained by time-series regressions, where the excess return of portfolio i, $R_{i,t+1}$ is regressed on a vector of risk factors, h_{t+1}:

$$R_{i,t+1} = \alpha_i + \beta_i' h_{t+1} + e_{i,t+1} \tag{5.2}$$

where $e_{i,t+1}$ is an error term. The risk prices, lambda, are estimated by a cross-sectional regression, while substituting all n portfolios' estimated betas $\hat{\beta}_i$ into equation (5.1).

Basic expected return models assume that both factor betas and risk prices are constant. However, if expected returns change over time to reflect changes in underlying economic states, factor betas and/or risk prices need to vary over time. Adrian et al. (2015) propose a general approach to estimate time-varying betas and risk prices. First, this study focuses on time-varying risk prices and estimates a model with constant betas but time-varying risk prices. This model is:

$$R_{i,t+1} = \beta_i' \lambda_0 + \beta_i' \Lambda_1 F_t + \beta_i' u_{t+1} + e_{i,t+1} \tag{5.3}$$

where λ_0 and Λ_1 are risk price parameters, F_t is the vector of forecast factors, and u_{t+1} is the innovations to risk factors. This study assumes no-arbitrage, which implies $\alpha_i = \beta_i' \lambda_0$. The first two terms in the right hand side of equation (5.3) are the expected returns, the third term is the component conditionally correlated with the innovations, and the last term represents the pricing errors. There are two key differences between equations (5.2) and (5.3). First, the forecast factors, F_t, are introduced to reflect predictability of carry trades. Second, the innovations to the risk factors are employed instead of risk factors,

h_{t+1}, since innovation components capture uncertainty in investment opportunities, and hence these components are linked to risk prices (Campbell, 1996 and Petkova, 2006).

The innovation term u_{t+1} in equation (5.3) is obtained by a Vector Autoregressive (VAR) approach. This study follows Adrian et al. (2015) and assumes X_{t+1} is a $K \times 1$ vector of state variables at $t+1$ and contains three types of variables. The first is $X_{1,t+1} \in \mathbb{R}^{K_1}$, which are risk factors only, used to price the cross-section of returns. The second is $X_{2,t+1} \in \mathbb{R}^{K_2}$, which are risk and forecast factors both used to price the cross-section of returns and to forecast the risk factors. Finally, $X_{3,t+1} \in \mathbb{R}^{K_3}$ are forecast factors only. The number of factors is denoted by: $K_C = K_1 + K_2$, $K_F = K_2 + K_3$, and $K = K_1 + K_2 + K_3$ where the subscript C indicates cross-section and the subscript F denotes forecast factors. The VAR dynamics are written as:

$$X_{t+1} = \mu + \Phi X_t + v_{t+1}, \tag{5.4}$$

where μ and Φ are coefficient vectors, v_{t+1} is the innovations vector and the first K_c columns of v_{t+1} are written as u_{t+1}. The aim is to obtain the time-varying risk prices $\lambda_0 + \Lambda_1 F_t$ in equation (5.3). To this end, this study needs to estimate both the factor betas, β_i, and the risk price parameters, λ_0 and Λ_1. Following Adrian et al. (2015), a three-step approach is employed. In the first step, the VAR system equation (5.4) is run and $\hat{u}_{t+1}$ is extracted. In the second step, $\hat{u}_{t+1}$ is substituted into equation (5.3) and the estimated betas, $\hat{\beta}_i$, and the predictive slopes, $\hat{w}_0$ and $\hat{w}_1$, are obtained. The predictive slopes, w_0 and w_1, are:

$$w_0 = \beta_i \lambda_0, w_1 = \beta_i \Lambda_1. \tag{5.5}$$

Finally, the risk price parameters, $\hat{\lambda}_0$ and $\hat{\Lambda}_1$, are obtained by substituting $\hat{\beta}_i$,

$\hat{w}_0$, and $\hat{w}_1$ into equation (5.5). Adrian et al. (2015) show that these estimated risk price parameters, $\hat{\lambda}_0$ and $\hat{\Lambda}_1$, converge to the limiting normal distribution, and they derive the variance which takes into account estimation uncertainty of the innovations term and factor betas.

As the risk prices are time-varying, they depend upon the forecast factors, F_t. This study tests whether a sample average of risk prices for given pricing factors, $\bar{\lambda}$, is significantly different from zero. This is obtained as:

$$\bar{\lambda} = \lambda_0 + \Lambda_1 E[F_t]. \tag{5.6}$$

$\bar{\lambda}$ converges to the limiting normal distribution, as shown by Adrian et al. (2015). Their closed form variance is used to conduct statistical inference.[7] This section described the constant beta and time-varying risk price model. The next section allows for time-varying betas.

5.2.2 Time-varying Betas and Time-varying Risk Prices

This section now describes the time-varying beta and risk price model proposed by Adrian et al. (2015). The factor betas (β_i) in equation (5.3) and the coefficients of the VAR (Φ and μ) in equation (5.4) follow smooth functions as in Ang and Kristensen (2012). These are given by:

$$\beta_{i,t} = \beta_i(t/T) + o(1),\ \mu_{i,t} = \mu_i(t/T) + o(1),\ \Phi_t = \Phi(t/T) + o(1), \tag{5.7}$$

where $o(1)$ is a smaller order term and $t = 1, 2, \ldots, T$. These functions are estimated nonparametrically and this approach is more robust to a misspecification problem, as pointed out by Harvey (2001). Moreover the assumption

[7] Further detail is described in Adrian et al. (2015) Appendix D.

that betas vary at a moderate level is consistent with the findings of Ghysels (1998) in the stock market context.

The coefficients of the VAR model in equation (5.4) are estimated by kernel weighted least squares regressions:

$$(\hat{\mu}_{t-1}, \hat{\Phi}_{t-1})' = \left(\sum_{s=1}^{T} K_b((s-t)/T) \tilde{X}_{s-1} \tilde{X}_{s-1}' \right)^{-1} \times \left(\sum_{s=1}^{T} K_b((s-t)/T) \tilde{X}_{s-1} X_s' \right) \tag{5.8}$$

where $\tilde{X}_{s-1} = (1, X_{s-1}')'$, $K_b(x) = K(x/b)$ for a kernel function $K(\cdot)$. This kernel estimation provides the time-varying coefficients. This study chooses the Gaussian density used by Ang and Kristensen (2012) and Adrian et al. (2015). The bandwidth denoted by $b \in (0, 1)$ is critical for estimation. A small bandwidth means only data close to t are used. Following Kristensen (2012) and Ang and Kristensen (2012), a plug-in bandwidth method is employed, since they report that cross-validation (CV) procedures show an extremely small bandwidth. This study uses a different bandwidth for each element of X_s, because each variable has different variation and curvature of the coefficients.

Time-invariant predictive slopes, w_0 and w_1, and factor betas, β_i, in equation (5.3) are also replaced with time-varying variables. The time-varying predictive slopes and the factor betas are obtained by the following weighted least squares regressions:

$$(\hat{w}_{0,i,t-1}, \hat{w}_{1,i,t-1}', \hat{\beta}_{i,t-1}') = \left(\sum_{s=1}^{T} K_h((s-t)/T) z_s^{tv} z_s^{tv\prime} \right)^{-1} \times \left(\sum_{s=1}^{T} K_h((s-t)/T) z_s^{tv} R_{i,s} \right) \tag{5.9}$$

where $z_s^{tv} = (1, X'_{s-1}, C'_s)'$ and $C_s = (X_{1,s}, X_{2,s})$, and $R_{i,s}$ is the return of portfolio i. Instead of the innovation term, which is employed in the constant beta model, the risk price factor vector, C_s, is used. This change is based on a technical aspect to satisfy uniform convergence.[8] Using the estimation results in equations (5.8) and (5.9), the risk price parameters, Λ^{tv}, are obtained as:

$$vec(\hat{\Lambda}^{tv}) = \left(\sum_{t=0}^{T-1} (\hat{F}_t \hat{F}_t' \otimes \hat{B}_t \hat{B}_t' + \rho_T)^{-1} \sum_{t=0}^{T-1} (\hat{F}_t \otimes \hat{B}_t')(R_{t+1} - \hat{B}_t \hat{u}_{t+1}) \right) \quad (5.10)$$

where $vec(\cdot)$ is the vectorization operator, $\otimes$ is the Kronecker product, $\hat{B}_t$ is the factor beta matrix that stacks $\beta_{i,t}$, $\hat{F}_t = (1, F_t')'$, and ρ_T is a positive sequence that satisfies $\rho_T \to 0$. u_{t+1} is obtained by the VAR with the weighted least squares coefficients in equation (5.8). Adrian et al. (2015) show that Λ^{tv} converges to the limiting normal distribution. When the factor betas are time-varying, the sample average of risk prices in equation (5.6) is changed to:

$$\bar{\lambda} = \lambda_0 + \Lambda_1 \cdot \lim_{T \to \infty} T^{-1} \sum_{T}^{t=1} E[F_t]. \quad (5.11)$$

$\bar{\lambda}$ also converges to the limiting normal distribution, as described in the constant beta model. Having set out the empirical method, the data is introduced next.

5.3 Data

This section explains the data in this section and begins with currency portfolio data. Spot and one month forward exchange rates are obtained from Datastream. In total 48 currencies are used, and this dataset is similar to that used by Menkhoff et al. (2012a). The base currency is the U.S. dollar, and the

[8]Lemma D.1. (c) and (d) in Adrian et al. (2015) is derived from the result of Kristensen (2009).

dataset extends from November 1983 to December 2013. As data availability for some currencies does not extend back to November 1983, the total number of exchange rates varies during the sample period. Six currency portfolios are constructed based on the forward discount as in Lustig et al. (2011). This study assumes that the covered interest rate parity holds and a positive forward discount means that the foreign interest rate is higher than the domestic interest rate (see Akram et al., 2008). This study denotes by P1(P6) the lowest (highest) interest rate currency portfolio. Following Lustig et al. (2011), trading costs are accounted for using bid-ask spreads.[9] Data are pre-treated using the method of Darvas (2009). He uses the previous day's data when there is no difference between bid and ask prices, or when the spread of the forward rates is smaller than that of the spot rates. 15 developed country currencies are constructed, since some high interest rate emerging currencies may have a disproportionate impact on the results. Lustig et al. (2011) and Menkhoff et al. (2012a) employ the same approach and they construct, both all countries', and developed countries' portfolios.

This chapter's risk factors are the dollar (DOL) and carry (HML_{FX}) factors introduced by Lustig et al. (2011). The dollar factor is computed as the average return of the currency portfolios. It acts as a market factor, as in the stock market literature, and the loadings on this factor are almost equal across currency portfolios. This factor is highly correlated with the first principal component of currency portfolio returns. The carry factor is computed as the return spread between high and low interest rate portfolios (P6−P1). This factor determines the cross-sectional return difference across currency portfolios. Lustig et al. (2011) demonstrate that this factor mimics the second principal component of currency portfolio returns.

[9] A bid rate is used when buying and an ask rate is used when selling a currency.

Next, this section turns to the three forecast factors. These set out the underlying conditions in the economy. The first is the global FX market volatility analysed by Menkhoff et al. (2012a). It is computed from daily returns for all currencies, and the monthly values are taken as the average of daily values. Let a daily log return of currency j on day τ be $r_{j,\tau} = s_{j,\tau} - s_{j,\tau-1}$, where $s_{j,\tau}$ is the log of the spot exchange rate on day τ. Global FX volatility, $\sigma_{FX,t}$, in month t is estimated as:

$$\sigma_{FX,t} = \frac{1}{T_t} \sum_{\tau=1}^{T_t} \sum_{j=1}^{K_\tau} \left(\frac{|r_{j,\tau}|}{K_\tau} \right) \tag{5.12}$$

where $|r_{j,\tau}|$ is the absolute value of $r_{j,\tau}$, K_τ is the number of currencies on day τ, and T_t is the total number of trading days in month t. This study does not take innovations as in Menkhoff et al. (2012a), since the time-varying model takes into account innovations in the VAR model. Menkhoff et al. (2012a) use the global FX volatility innovations as a risk factor, but this study adopts it as a forecast factor as in Christiansen et al. (2011), Bakshi and Panayotov (2013), and Cenedese et al. (2014). However, this study also checks in the robustness test section whether this factor acts as a risk factor.

The second forecast factor is a commodity price return. Following Bakshi and Panayotov (2013), the Raw Industrials subindex of the CRB Spot Commodity Index is adopted. Monthly returns are used, since the portfolios are constructed at monthly frequency. The third variable is market liquidity for which the TED spread is used. Brunnermeier et al. (2009) show that the TED spread is related to the future return of currency carry trades, and Mancini et al. (2013) and Karnaukh et al. (2015) show that it is strongly related to FX market liquidity. The TED spread is computed as the difference between the three month Eurodollar LIBOR rate and the three month Treasury Bill rate.[10]

5.4 Empirical Results

5.4.1 Estimated Factor Betas

This section begins the presentation of the empirical results with factor betas, which represent exposures on risk factors for each portfolio. Table 5.1 provides constant beta estimates from equation (5.3). The beta estimates on the dollar factor (DOL) show that all portfolios have almost the same exposure to this factor, implying that this factor does not account for cross-sectional differences in returns across currency portfolios. In contrast, the estimated betas on the carry factor (HML_{FX}) increase monotonically from P1 to P6. This is evidence that the carry factor is important in pricing the cross-section currency portfolios, and high interest rate currency portfolios are more exposed to this factor. The results for developed countries reported in Panel B show similar patterns.

Next, this section compares these constant betas with time-varying betas. The time-varying betas are obtained by equation (5.9). For robustness, 36-month rolling betas are also estimated. The results of betas on the dollar factor are plotted in Figure 5.1, which clearly shows time variations in the betas. They move around the constant beta estimates, and this is consistent with the results of Adrian et al. (2015) for stock and bond portfolios. The fluctuations of the time-varying betas and rolling betas have a similar pattern, but the time-varying betas are less volatile, because they are obtained by the kernel smoothing method.

[10]This study cannot cover the entire sample period by LIBOR, thus this study employs the three-month interbank rate in the U.S. to cover a longer period.

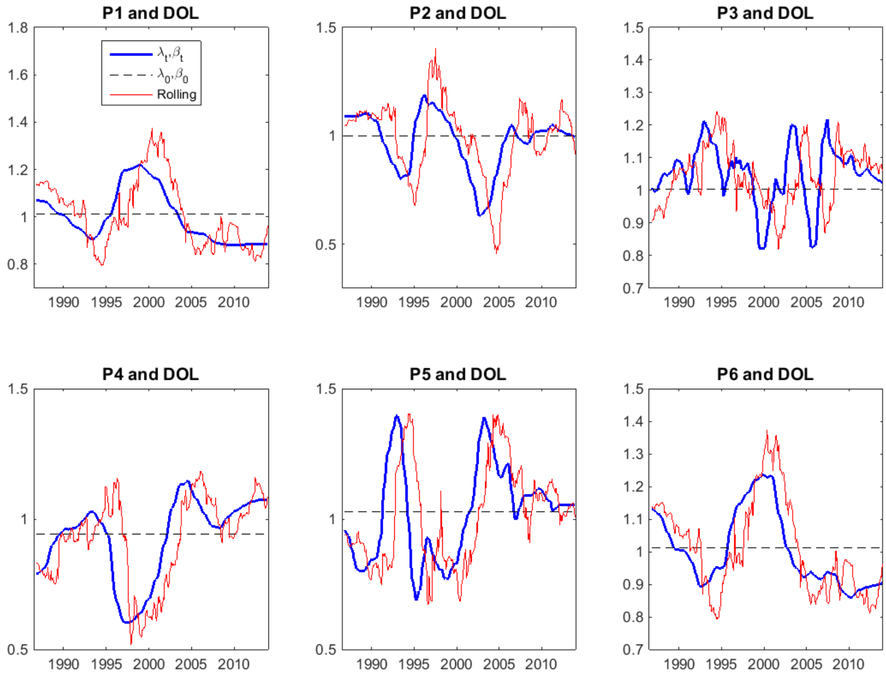
TABLE 5.1: Beta Estimate to Risk Factors DOL and HML_{FX}: Constant Beta Model

Panel A: All countries				
Portfolio	β_{DOL}	s.e.	β_{HML}	s.e.
P1	1.01***	(0.02)	-0.44***	(0.03)
P2	1.00***	(0.02)	-0.21***	(0.03)
P3	1.00***	(0.02)	-0.05***	(0.03)
P4	0.94***	(0.03)	0.06**	(0.03)
P5	1.03***	(0.03)	0.09**	(0.04)
P6	1.01***	(0.02)	0.56***	(0.03)

Panel B: Developed countries				
Portfolio	β_{DOL}	s.e.	β_{HML}	s.e.
P1	1.03***	(0.02)	-0.57***	(0.02)
P2	1.00***	(0.03)	-0.05*	(0.03)
P3	1.00***	(0.02)	0.02	(0.03)
P4	0.93***	(0.03)	0.18***	(0.03)
P5	1.03***	(0.02)	0.43***	(0.02)

Notes: This table presents estimated factor betas from the constant beta model. Factor betas for currency portfolios of carry returns are obtained by equation (5.3). The risk factors are dollar (DOL) and the return spread between high and low interest rate currency portfolios (HML_{FX}) as in Lustig et al. (2011). The test assets of Panel A are six forward discount sorted all country currency portfolios and those of Panel B are five forward discount sorted developed country currency portfolios. Asymptotic standard errors are reported in parentheses. The sample period is November 1983 to December 2013. Asterisk *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

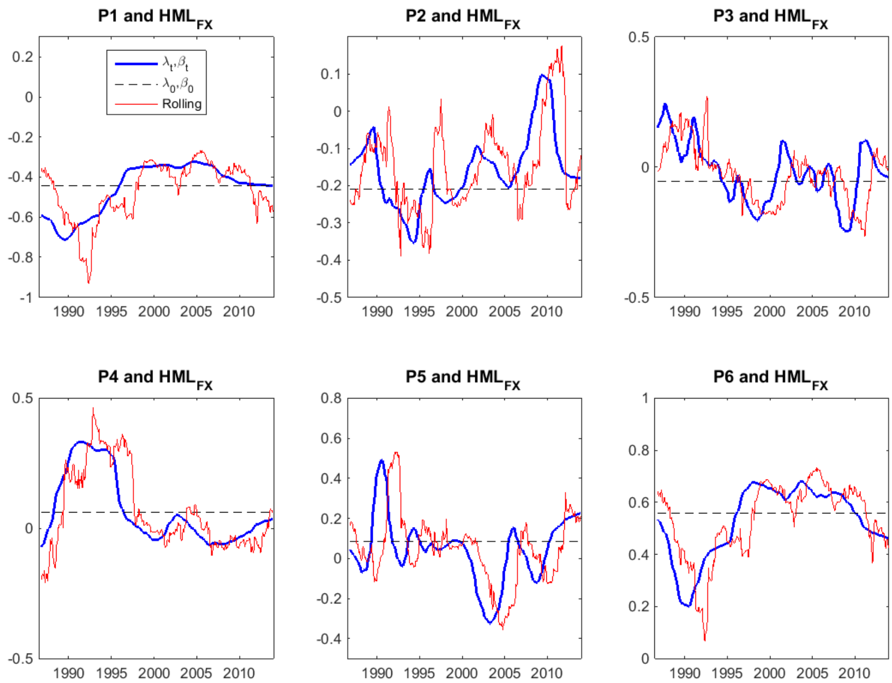
FIGURE 5.1: Comparison of time series portfolio betas on DOL



Notes:This figure provides plots of the estimated time series of betas on the dollar (DOL). λ_t, β_t denotes the time-varying risk price and beta model and the betas are obtained by equation (5.9) (thick blue line). λ_t, β_0 denotes the constant beta and time-varying risk price model and the betas are obtained by equation (5.3) (dashed black line). Rolling denotes the 36 months rolling window beta (thin red line).

Figure 2 plots the constant and time-varying betas on the carry factor estimated by equations (5.3) and (5.9). Portfolio P1 always has negative, and P6 positive, exposure to the carry risk.[11] We can see that currency portfolios are more sensitive to the carry factor than to the dollar factor. Note that a change in beta does not necessarily lead to a decline in the expected carry return, since returns depend upon both betas and risk prices. If risk prices change over time, this may have an impact on expected returns.

FIGURE 5.2: Comparison of time series portfolio betas on HML_{FX}



Notes:This figure provides plots of the estimated time series of betas on the return spread between high and low interest rate currency portfolios (HML_{FX}). λ_t, β_t denotes the time-varying risk price and beta model and the betas are obtained by equation (5.9) (thick blue line). λ_t, β_0 denotes the constant beta and time-varying risk price model and the betas are obtained by equation (5.3) (dashed black line). Rolling denotes the 36 months rolling window beta (thin red line).

[11] The definition of the carry factor is directly related to P1 and P6, the fluctuations of these portfolios are similar.

5.4.2 Estimated Risk Price Parameters

Next, this section investigates possible relations between the forecast and risk factors. While the results in the previous subsection provide evidence of time-varying betas, risk prices also may vary over time. This study investigates which time variation matters most for the carry trade pricing model. To this end, this study needs to link risk prices and forecast factors, because forecast factors generate time variations of risk prices. Risk price parameters are key elements for the links, since time-varying risk prices are obtained by the product of risk price parameters and forecast factors ($\Lambda_1 F_t$). Note that the risk price parameters are constant while the risk prices vary through changes in the forecast factors.

Table 5.2 reports estimates of risk price parameters, λ_0 and Λ_1, from equation (5.5) based on the three forecast factors mentioned above: global FX volatility (VOL_{FX}), commodity price return (CRB), and market liquidity (TED). Average risk prices $\bar{\lambda}$ from equation (5.6) are presented. This study begins on Panel A of Table 5.2 with the constant beta and time-varying risk price model for all country results. If time-varying risk prices are more important, mistakenly imposing time-varying betas may distort estimated risk price parameters. This study finds the market liquidity forecast variable is important for the dollar factor, and the FX volatility forecast variable plays a main role in generating carry factor fluctuations. The negative relation between the dollar factor and the market liquidity illustrates that when market liquidity dries up (TED rises), most currencies depreciate against the U.S. dollar. The strong relation between the U.S. dollar and the market liquidity comes from the risk haven characteristic of the U.S. dollar. When currency markets crash, investors shift their allocations from emerging currencies to the U.S. dollar (McCauley and

McGuire, 2009). This study also observes that the FX market volatility variable is strongly related to the carry factor. High FX volatility leads to low risk price on the carry factor, indicating that market uncertainty induces investors to unwind their carry positions. This result is related to the findings of Bakshi and Panayotov (2013) and Cenedese et al. (2014) who report that volatility in FX markets contains information for future carry trade returns, but the results suggest that volatility generates fluctuations in the risk price. The time series average risk price, $\bar{\lambda}$, on the dollar factor does not differ from zero, while that on the carry factor is statistically significant at the 1% level.

This study now turns to the time-varying beta model that reflects investor changes in factor exposure. The results are reported in Panel C of Table 5.2. The risk price parameters are estimated by equation (5.10) and the average risk price is obtained by equation (5.11). This study observes a similar pattern in that the market liquidity forecast variable is substantial for the dollar factor and the FX volatility forecast variable is important for the carry factor. Interestingly, most standard errors of the time-varying beta model are smaller than those of the constant beta model. Adrian et al. (2015), who analyse the stock and bond markets, argue that these smaller standard errors are an advantage of the time-varying beta model. Importantly, the average risk price of the dollar is statistically significant at the 5% level and, thus, the dollar factor commands a risk premium. This is direct contrast to the results of the constant beta model and the previous literature, such as Lustig et al. (2011) and Menkhoff et al. (2012a). This finding highlights the difference between time-varying and constant betas. The time-varying betas generate heterogeneous factor exposures across portfolios and create a statistically significant risk price on the dollar factor in currency portfolios. However this study does not obtain heterogeneous factor exposures with constant betas. This is related to the result of Verdelhan (2015) who shows that the dollar factor bears a risk premium.

TABLE 5.2: Risk Price Parameter Estimates on Forecast Factors

	Risk Factor	λ_0	Forecast Factors VOL_{FX}	CRB	TED	$\bar{\lambda}$
Constant beta and time-varying risk price model						
Panel A: All countries						
(a)	DOL	0.63	-0.35	0.07	-0.60**	0.18
		(0.41)	(0.94)	(0.05)	(0.31)	(0.14)
	HML_{FX}	2.00***	-3.10***	0.08*	-0.45	0.49***
		(0.39)	(0.91)	(0.04)	(0.30)	(0.14)
Panel B: Developed countries						
(b)	DOL	0.52	0.06	0.08	-0.71**	0.19
		(0.47)	(0.94)	(0.05)	(0.34)	(0.16)
	HML_{FX}	2.02***	-2.65***	0.03	-0.84**	0.34**
		(0.47)	(0.95)	(0.05)	(0.34)	(0.17)
Time-varying beta and time-varying risk price model						
Panel C: All countries						
(c)	DOL	0.72*	-0.43	0.07*	-0.57**	0.25**
		(0.37)	(0.86)	(0.04)	(0.28)	(0.11)
	HML_{FX}	1.98***	-3.01***	0.04	-0.52*	0.46***
		(0.39)	(0.88)	(0.04)	(0.29)	(0.11)
Panel D: Developed countries						
(d)	DOL	0.47	0.30	0.09*	-0.69**	0.27**
		(0.43)	(0.86)	(0.05)	(0.31)	(0.12)
	HML_{FX}	1.98***	-2.64***	0.03	-0.85***	0.30**
		(0.43)	(0.85)	(0.04)	(0.31)	(0.12)

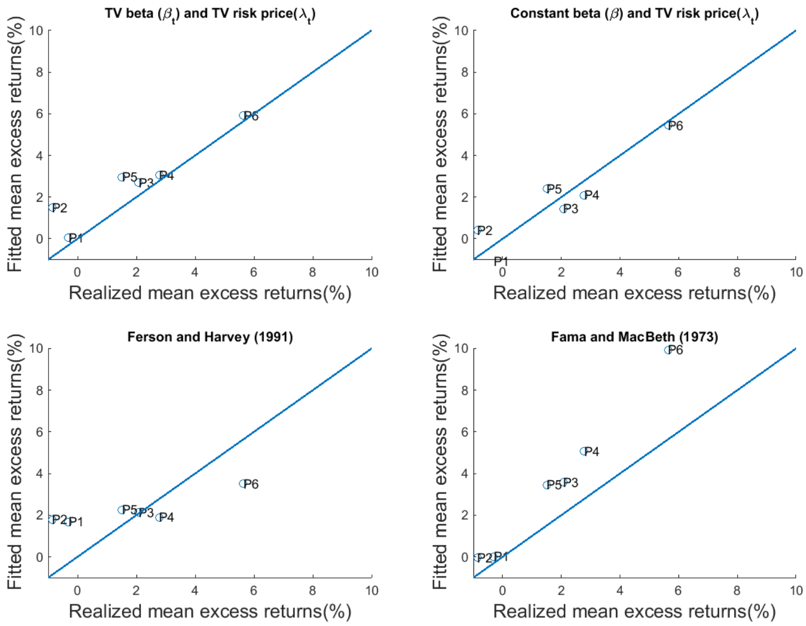
Notes: This table presents risk price parameter estimates on forecast factors, global FX volatility (VOL_{FX}), commodity price (CRB), and market liquidity (TED). The risk price parameters estimates using constant betas are from equation (5.5) in Panels A and B. The approach to estimate risk price parameters for time-varying betas are equation (5.10) in Panels C and D. Risk price parameters show relationships between risk and forecast factors, and risk prices are computed as risk price parameters time forecast factors. These methods are from Adrian et al. (2015). The average risk price $\bar{\lambda}$ in Panels A and B is obtained by equation (5.6) and $\bar{\lambda}$ in Panels C and D is obtained by equation (5.11). The risk factors are the dollar (DOL) and the return spread between high and low interest rate currency portfolios (HML_{FX}) as in Lustig et al. (2011). The forecast factors are global FX volatility (VOL_{FX}) as in Menkhoff et al. (2012a), CRB Raw industrial material subindex return (CRB) as in Bakshi and Panayotov (2013), and TED spread (TED). Heteroskedasticity robust standard errors are reported in parentheses. The test assets of Panels A and C are six forward discount sorted all country currency portfolios and those of Panels B and D are five forward discount sorted developed country currency portfolios. The sample period is November 1983 to December 2013. Asterisk *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Verdelhan (2015) employs dollar sorted currency portfolios to estimate heterogeneous factor exposures while betas are constant over time. The time-varying beta model provides heterogeneous factor exposures without adopting dollar sorted currency portfolios.

The same estimation is repeated using developed countries in Table 5.2. Although the main findings are similar to those of the all countries' results, there are two differences. The market liquidity variable is now related to both the dollar and carry factors, which implies that institutional investors use the currencies of developed countries, and funding constraints may play an important role in the developed countries' sample as reported by Habib and Stracca (2012). Further, the average risk price of the carry factor in developed countries is smaller than that in all countries. In other words, the estimated $\bar{\lambda}$ on the carry factor is smaller in Panels B and D, reflecting that emerging currencies typically have higher interest rates, since emerging countries tend to have relatively high inflation ratios.

In summary, this study finds the risk price parameter on the market liquidity forecast variable is associated with the dollar factor, and the FX market volatility forecast variable is linked to the carry factor through the risk price parameter. Changes in the market liquidity variable produce time variation in the dollar factor, and changes in the FX market uncertainty variable cause time variation in the carry factor. This study finds statistically significant relations between risk prices and forecast factors in both the time-varying and the constant beta models. The next section investigates the pricing errors of these models.

FIGURE 5.3: Comparison of cross-sectional pricing models



Notes: This figure displays pricing errors for asset pricing models. The realized mean excess returns ($r_{i,t}$) are on the horizontal line and the mean fitted excess returns are on the vertical line. Both excess returns are annualized returns. The risk factors are dollar (DOL) and the return spread between high and low interest rate currency portfolios (HML_{FX}) as in Lustig et al. (2011). The forecast factors are global FX volatility (VOL_{FX}) as in Menkhoff et al. (2012a), CRB Raw industrial material subindex return (CRB) as in Bakshi and Panayotov (2013), and TED spread (TED). The upper-left graph shows the time-varying beta and risk price model, the upper-right graph shows the constant beta and time-varying price model, the lower-left graphs shows the Ferson and Harvey (1991) approach, which uses 36 months rolling regressions, and the lower-right graph shows the Fama and MacBeth (1973) approach, which uses 36 months rolling regressions.

5.4.3 Pricing Errors

Having found the factor betas vary over time, and the forecast factors add time variation to the risk prices, this section investigates which time variations matter more in terms of the carry pricing model. This section does so by examining the pricing errors of the respective models through plots of realized mean returns against fitted mean returns. Does time variation in the parameters have implications on the size of these errors? Figure 5.3 provides a visual comparison across the estimation results. The realized mean excess returns of P1 to P6 are on the x-axes and the predicted mean excess returns by a model are on the y-axes. Perfect prediction would imply all six portfolios plotting exactly on the 45-degree line. The upper-left graph displays the result of the time-varying beta and risk price model, and it shows that all predicted returns are close to the 45-degree line. The second portfolio, P2, however, has the largest pricing error, and this model slightly over predicts all portfolio returns. The constant beta and time-varying risk price model of Adrian et al. (2015) shows a better performance in the upper-right graph. The pricing error of P2 is smaller than that of the time-varying beta and time-varying risk price model. In contrast, conventional linear approaches, such as Fama and MacBeth on the bottom-right panel of Figure 5.3 and Ferson and Harvey (1991) (bottom-left graph), exhibit larger pricing errors. Both these conventional models estimate the betas and the risk prices using 36-month rolling regressions.

Accordingly, a carry model with time-varying risk prices dominates alternatives visually, hence this study further assesses the pricing errors of each portfolio using the Mean Squared Errors (MSE). Table 5.3 presents the average MSE of each portfolio and the last row displays the average of all portfolios. The time-varying risk price models in columns (a) and (b), exhibit smaller

MSEs than those of rolling methods in columns (e) and (f). Comparing time-varying risk price models, this study observes that the constant beta and time-varying risk price model has the smallest average MSE, suggesting that time variation in risk prices is more important than time variation in betas in pricing carry trade portfolios. Ghysels (1998) states that misspecification causes overestimation of betas. Investors overreact as they cannot observe a true relationship between changes in economic states and carry returns. This overreaction is plausible for carry trade investors, since these investors know that carry trades contain large downside risk and adjust their portfolio allocations to avoid crashes in FX markets.

5.4.4 Interpretation of Time Variation

Given the importance of time variation in risk prices shown in the above results, this section now investigates further these dynamics. Figure 5.4 plots the time evolution of the risk prices of the dollar and the carry factors. The time variation of the dollar price, with 95% confidence intervals, is reported in the upper graph. This is computed as the risk price parameter, λ_0, plus the product of the risk price parameters with the forecast factors, $\Lambda_1 F_t$. The figure shows that the confidence interval is slightly above zero during the middle of the 1990s and 2000s, and there is a substantial drop at the global financial crisis in 2008. The lower graph shows the time variation of the carry factor. The confidence interval is clearly above zero during most periods, and during the crisis, the risk price collapses to -5% per month, which is almost ten times larger in absolute value than that of the average risk price. Increases in FX volatility and market liquidity during the crisis cause the sign of the risk price to flip, because both forecast factors are negatively related to the carry

TABLE 5.3: Mean Squared Pricing Error for Time-varying or Constant Factor Betas and Risk Prices

Panel A						
All countries	(a)	(b)	(c)	(d)	(e)	(f)
Factor betas(β)	TV	C	T	C	FH	FM
Risk prices(λ)	TV	TV	C	C	FH	FM
P1	0.92	0.74	1.05	0.79	1.16	1.05
P2	1.06	0.90	1.14	0.91	1.17	1.14
P3	0.97	0.79	0.98	0.84	1.04	0.98
P4	1.02	0.87	1.16	1.02	1.23	1.16
P5	1.22	1.02	1.31	1.13	1.41	1.31
P6	0.99	0.76	1.49	1.16	1.54	1.49
Average	1.03	0.85	1.19	0.97	1.26	1.19

Panel B						
Developed countries	(a)	(b)	(c)	(d)	(e)	(f)
Factor betas(β)	TV	C	TV	C	FH	FM
Risk prices(λ)	TV	TV	C	C	FH	FM
P1	1.28	0.84	1.25	0.89	1.31	1.41
P2	1.38	1.28	1.49	1.32	1.56	1.62
P3	1.24	0.98	1.28	1.09	1.36	1.38
P4	1.36	1.10	1.34	1.24	1.44	1.43
P5	1.17	0.79	1.37	1.10	1.49	1.52
Average	1.29	1.00	1.35	1.13	1.43	1.47

Notes: This table presents the mean squared pricing error across various models. Smaller pricing errors are indicative of better fitting models. TV is the time-varying and C is the constant parameter model. FH denotes the Ferson and Harvey (1991) procedure using 36 months rolling regressions, and FM denotes the Fama and MacBeth (1973) procedure using 36 months rolling regressions. Model (b) with time-varying risk prices but constant betas has the smallest pricing errors, indicating the best fit. The test assets of Panel A are six forward discount sorted all country currency portfolios and those of Panel B are five forward discount sorted developed country currency portfolios. The risk factors are dollar (DOL) and the return spread between high and low interest rate currency portfolios (HML_{FX}) as in Lustig et al. (2011). The forecast factors are global FX volatility (VOL_{FX}) as in Menkhoff et al. (2012a), CRB Raw industrial material subindex return (CRB) as in Bakshi and Panayotov (2013), and TED spread (TED). The sample period is November 1986 to December 2013.

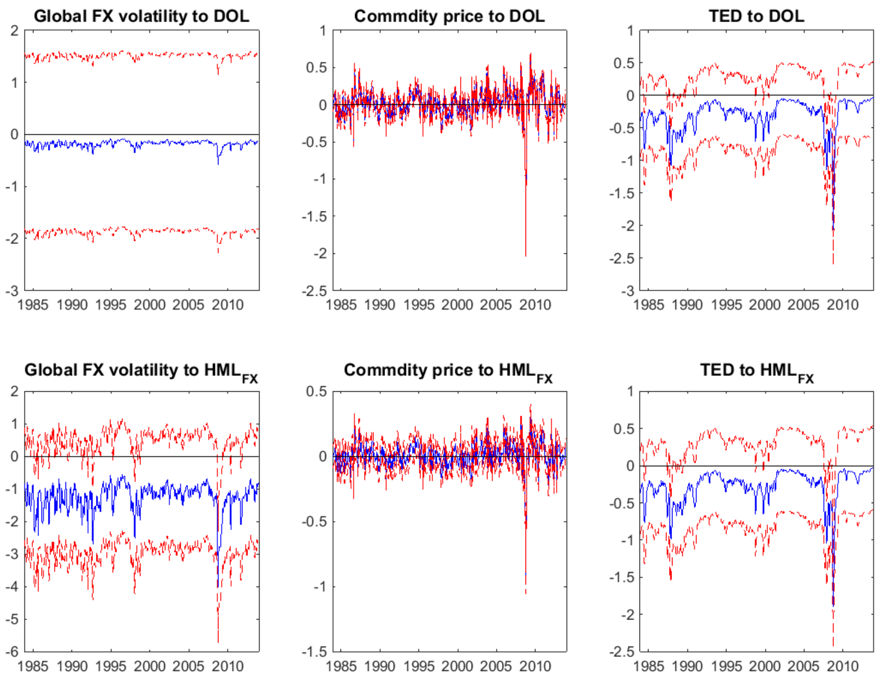
factor, as reported in Table 5.2. Market uncertainty and lack of liquidity induce unwinding of carry positions and in favor of safer assets such as the U.S. dollar.

FIGURE 5.4: Time-varying risk prices (λ) of DOL and HML_{FX}

This figure displays time series risk prices of the dollar (DOL) and the return spread between high and low interest rate currency portfolios (HML_{FX}) with their 95% confidence intervals. The risk price is obtained as the risk price parameter (λ_0) plus the risk price parameters (Λ_1) multiplied by the time forecast factors (F_t), $\lambda = \lambda_0 + \Lambda_1 F_t$. Three forecast factors are global FX volatility (VOL_{FX}) as in Menkhoff et al. (2012a), CRB Raw industrial material subindex return (CRB) as in Bakshi and Panayotov (2013), and TED spread (TED).

Figure 5.5 plots the contribution of each forecast factor. These are obtained by computing the product of the risk price parameter with a particular forecast factor, $\lambda_{1,j} F_{j,t}$, where $\lambda_{1,j}$ is the $(1, j)$ element of the risk price parameter vector and $F_{j,t}$ is the j-th forecast factor. The scale of the y-axes shows the contribution of each forecast factor. The upper three graphs indicate that the main contribution to the dollar factor comes from the market liquidity forecast variable. The lower three graphs show that FX market volatility is the most important contributor to the carry factor. However, we see the market liquidity and the commodity price variables have substantial impact during the crisis. Interestingly, the market liquidity variable is important only when liquidity dries up significantly. This is due to liquidity spirals, as shown by Brunnermeier and Pedersen (2009). All investors demand liquidity and it generates the negative risk price on the carry factor.

FIGURE 5.5: Contribution of forecast factors



Notes: This figure displays the contribution of the three forecast factors with their 95% confidence intervals. The contribution is estimated as the risk price parameter times the forecast factor, $\lambda_{1,j} F_{j,t}$. The forecast factors are global FX volatility (VOL_{FX}) as in Menkhoff et al. (2012a), CRB Raw industrial material subindex return (CRB) as in Bakshi and Panayotov (2013), and TED spread (TED).

5.5 Robustness

5.5.1 Excluding the Global Financial Crisis

The analyses presented in the previous section show that the global financial crisis affects the estimation of risk prices. For robustness, the same estimations are repeated using data before the crisis only. If these provide different results, this study would be able to confirm the importance of the crisis and, consequently, the appropriateness of the time-varying risk price methodology. Table D.5 in the Appendix presents the estimation results for the pre-crisis period from November 1983 to March 2008. From Panels A and C, we see a weakening relation between the market liquidity variable and the dollar factor, and the average risk prices on the dollar and the carry factors have higher values. For example, using the time-varying beta and risk price model, the average risk price on the carry factor prior to the crisis is 0.50, compared to 0.46 for the full sample period. Surprisingly, Panel D shows that all estimated risk price parameters are insignificant when this study analyses the developed country sample. As Farhi and Gabaix (2016) highlight the importance of disaster risk in generating a positive carry trade return, the empirical results consequently show disaster risk is significantly related to carry trade returns. The plots of risk prices in Figure D.6 for the pre-crisis sample also display different shapes to those presented in Figure 5.4 for the full sample. In particular, the variation over time in risk prices is smaller. Overall, these results confirm the existence of time-varying risk prices and the importance of the crisis period.

5.5.2 FX Volatility Innovation Factor

Also for robustness, another factor model is estimated. Following Menkhoff et al. (2012a), this section builds a factor model using the dollar and the FX volatility innovation factors. In contrast to Menkhoff et al. (2012a), however, the proposed model allows for time variation in betas and risk prices. To this end, the carry factor is replaced by an FX volatility innovation factor computed by a return-based mimicking portfolio in a similar manner to how the carry factor was constructed. Table 5.4 reports that the estimation results, together with those of a constant beta and a time-varying beta models.

The basic findings are similar to those reported in Table 5.2. For example, from Panel C in Table 5.4, the two forecast variables, FX market volatility and market liquidity, positively impact on the FX volatility innovation factor. This implies that increases in FX market volatility or the TED spread lead to increases in the risk price of the volatility innovation factor. The average risk price on the FX volatility innovation factor is negative, and the risk exposure to this factor is positive for P1 and negative for P6, and hence P1 works as a hedge when FX volatility is high. The Appendix (Figure D.5) reports the time variation of the volatility risk price. The price is negative for most periods but suddenly jumps during market turmoil. In particular, the most significant jump is observed during the global financial crisis. In summary, this section finds the time-varying risk price model clearly highlights the time variation of the FX volatility innovation factor.

5.5.3 Carry and Momentum Portfolios

As a further robustness exercise this section also includes momentum strategy currency portfolios as test assets. Lewellen et al. (2010) propose to include portfolios sorted by other characteristics, when test portfolios have a factor structure. Following Menkhoff et al. (2012b), six (five) currency momentum portfolios for the all (developed) countries' sample are constructed. The currencies are sorted by one month lagged excess returns, and this section takes

TABLE 5.4: Risk Price Parameter Estimates on Forecast Factors: FX Volatility Innovations

	Risk Factor	λ_0	VOL_{FX}	CRB	TED	$\bar{\lambda}$
			Forecast Factors			
Constant beta and time-varying risk price model						
Panel A: All countries						
(a)	DOL	0.63	-0.36	0.07	-0.60*	0.18
		(0.41)	(0.94)	(0.05)	(0.31)	(0.14)
	ΔVOL_{FX}	-3.37***	4.97***	-0.17**	0.94*	-0.84***
		(0.67)	(1.55)	(0.07)	(0.51)	(0.25)
Panel B: Developed countries						
(b)	DOL	0.52	0.05	0.08	-0.71**	0.19
		(0.47)	(0.94)	(0.05)	(0.34)	(0.16)
	ΔVOL_{FX}	-2.89***	3.34**	-0.09	1.45***	-0.57**
		(0.70)	(1.40)	(0.07)	(0.50)	(0.25)
Time-varying beta and time-varying risk price model						
Panel C: All countries						
(c)	DOL	0.73*	-0.51	0.07	-0.56**	0.24**
		(0.38)	(0.88)	(0.04)	(0.28)	(0.12)
	ΔVOL_{FX}	-3.60***	5.04***	-0.12	1.14**	-0.92***
		(0.66)	(1.52)	(0.07)	(0.49)	(0.20)
Panel D: Developed countries						
(d)	DOL	0.49	0.25	0.08*	-0.68**	0.27**
		(0.42)	(0.83)	(0.04)	(0.30)	(0.12)
	ΔVOL_{FX}	-2.76***	3.20**	-0.09	1.41***	-0.53***
		(0.66)	(1.31)	(0.07)	(0.47)	(0.19)

Notes: This table presents risk price parameter estimates on forecast factors, global FX volatility (VOL_{FX}), commodity price (CRB), and market liquidity (TED). The risk price parameters estimates using constant betas are from equation (5.5) in Panels A and B. The approach to estimate risk price parameters for time-varying betas are equation (5.10) in Panels C and D. Risk price parameters show relationships between risk and forecast factors, and risk prices are computed as risk price parameters time forecast factors. These methods are from Adrian et al. (2015). The average risk price $\bar{\lambda}$ in Panels A and B is obtained by equation (5.6) and $\bar{\lambda}$ in Panels C and D is obtained by equation (5.11). The risk factors are the dollar (DOL) and the global FX volatility innovations (ΔVOL_{FX}) as in Menkhoff et al. (2012a). The forecast factors are global FX volatility (VOL_{FX}) as in Menkhoff et al. (2012a), CRB Raw industrial material subindex return (CRB) as in Bakshi and Panayotov (2013), and TED spread (TED). Heteroskedasticity robust standard errors are reported in parentheses. The test assets of Panels A and C are six forward discount sorted all country currency portfolios and those of Panels B and D are five forward discount sorted developed country currency portfolios. The sample period is November 1983 to December 2013. Asterisk *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

into account transaction costs, as is done thus far.

Table 5.5 presents the results using carry and momentum currency portfolios. Panel A reports the results of the constant beta and time-varying risk price model. These results correspond to the results of Panel A in Table 5.2. The main finding, that FX volatility is the main driver of the carry factor, remains the same, and the average risk price of the carry factor has the same magnitude. Table 5.5 Panels B, C, and D show that the main findings of Table 5.2 are not affected when momentum portfolios are included. FX volatility is related to the carry factor, and the average price of this factor is positive and statistically significant at least at the 5% level.

5.5.4 Up-side and Down-side Analysis

Given the large negative risk price at the crisis reported in Section 4, this section considers the interpretation of this result. Lakonishok et al. (1994) argue that if an investing strategy can be explained by a risk factor, the strategy should have negative returns in recessions. Also, Pettengill et al. (1995) and Hur et al. (2014) report a negative relationship between betas and risk prices in a downside stock market. The empirical results on carry trades support this relation, because the high interest rate currency portfolio has a positive beta on the carry factor, and the risk price varies over time. To confirm this relation, this section splits the data into two states as in Pettengill et al. (1995) and Hur et al. (2014). A down market state is defined as one in which the carry factor is negative, and an up market state is defined as one in which the carry factor is positive. The Fama and MacBeth regressions are then run for each state. Table 5.6 reports the results and column (a) presents the results for all the data as a benchmark, and the risk price on the carry factor is positive. In the results for the separate states, we observe a negative risk price in the down market state

TABLE 5.5: Risk Price Parameter Estimates on Forecast Factors: Carry and Momentum Portfolios

	Risk Factor	λ_0	VOL_{FX}	CRB	TED	$\bar{\lambda}$
			Forecast Factors			
Constant beta and time-varying risk price model						
Panel A: All countries						
(a)	DOL	0.65	-0.44	0.06	-0.59*	0.18
		(0.41)	(0.94)	(0.05)	(0.31)	(0.14)
	HML_{FX}	2.17***	-3.70***	0.08*	-0.40	0.43***
		(0.39)	(0.92)	(0.04)	(0.30)	(0.15)
Panel B: Developed countries						
(c)	DOL	0.52	0.01	0.08	-0.70**	0.18
		(0.47)	(0.94)	(0.05)	(0.34)	(0.16)
	HML_{FX}	1.77***	-2.04**	0.04	-0.88**	0.36**
		(0.48)	(0.97)	(0.05)	(0.34)	(0.16)
Time-varying beta and time-varying risk price model						
Panel C: All countries						
(b)	DOL	0.75**	-0.55	0.07*	-0.55*	0.25**
		(0.38)	(0.87)	(0.04)	(0.28)	(0.11)
	HML_{FX}	1.83***	-2.82***	0.02	-0.63**	0.33***
		(0.40)	(0.91)	(0.04)	(0.30)	(0.12)
Panel D: Developed countries						
(d)	DOL	0.50	0.21	0.09*	-0.68**	0.26**
		(0.43)	(0.86)	(0.05)	(0.31)	(0.12)
	HML_{FX}	1.41***	-1.54*	0.03	-0.75**	0.30**
		(0.42)	(0.84)	(0.04)	(0.30)	(0.12)

Notes: This table presents risk price parameter estimates on forecast factors, global FX volatility (VOL_{FX}), commodity price (CRB), and market liquidity (TED). The risk price parameters estimates using constant betas are from equation (5.5) in Panels A and B. The approach to estimate risk price parameters for time-varying betas are equation (5.10) in Panels C and D. Risk price parameters show relationships between risk and forecast factors, and risk prices are computed as risk price parameters time forecast factors. These methods are from Adrian et al. (2015). The average risk price $\bar{\lambda}$ in Panels A and B is obtained by equation (5.6) and $\bar{\lambda}$ in Panels C and D is obtained by equation (5.11). The risk factors are the dollar (DOL) and the return spread between high and low interest rate currency portfolios (HML_{FX}) as in Lustig et al. (2011). The forecast factors are global FX volatility (VOL_{FX}) as in Menkhoff et al. (2012a), CRB Raw industrial material subindex return (CRB) as in Bakshi and Panayotov (2013), and TED spread (TED). Heteroskedasticity robust standard errors are reported in parentheses.The test assets of Panels A and C are six forward discount and six past one month currency excess return sorted all country currency portfolios and those of Panels B and D are five forward discount and five past one month currency excess return sorted developed country currency portfolios. The sample period is November 1983 to December 2013. Asterisk *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

in column (b) and a positive risk price in the up market state in column (c). Moreover, the magnitude of the positive risk price is greater than that of the negative risk price, which implies a higher risk price in the up market state. Summarizing the up and down-state results in Table 5.6, this section confirms that the time variation of the risk price on the carry factor is associated with the state of the market.

TABLE 5.6: Fama and MacBeth Cross-Sectional Regressions for Down and Up Markets

	All	Down	Up
Panel A: All countries			
	(a)	(b)	(c)
DOL	0.18	0.05	0.26
	(0.12)	(0.22)	(0.14)
HML_{FX}	0.49***	-1.31***	1.65***
	(0.12)	(0.15)	(0.11)
R^2	0.86	0.82	0.90
Panel B: Developed countries			
	All	Down	Up
	(a)	(b)	(c)
DOL	0.19	0.30	0.12
	(0.13)	(0.23)	(0.17)
HML_{FX}	0.33**	-2.04***	1.86***
	(0.12)	(0.19)	(0.11)
R^2	0.53	0.93	0.95

Notes: This table presents risk prices for up and down markets estimated by the Fama and MacBeth (1973) methodology. The market is defined as a down market if $HML_{FX} < 0$, and an up market if $HML_{FX} > 0$ as in Pettengill et al. (1995). The test assets of Panel A are six forward discount sorted all country currency portfolios and those of Panel B are five forward discount sorted developed country currency portfolios. 'All' denotes both up and down markets. Shanken (1992) standard errors are reported in parentheses. The R^2 is a measure of fit between the sample mean of returns and the predicted mean returns. The sample period is November 1983 to December 2013. Asterisk *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

5.6 Conclusion

Expected returns for investors may vary over time as pointed out by Ferson and Harvey (1991) in the context of the stock and bond markets. These time-varying expected returns suggest that factor betas and/or risk prices change over time, since expected returns depend upon factor betas and risk prices. Ferson and Harvey (1991) and Adrian et al. (2015) decompose the change in expected returns and present evidence that time-varying risk prices are more important than time-varying betas for stock and bond markets.

Motivated by these studies in other asset classes, this chapter explores time-varying betas and risk prices in carry trades. Recently, several studies find carry trades to be predictable. For instance, Bakshi and Panayotov (2013) use commodity prices and Cenedese et al. (2014) adopt FX market volatility to predict carry trades. This predictability motivates the consideration of the time-varying beta and risk price model, since betas and/or risk prices vary over time to reflect changes in the investment environment. This chapter uses Adrian et al.'s (2015) approach that allows for time variations of betas and risk prices in the asset pricing model. Further, the time-varying beta and risk price approach explicitly incorporates forecast variables with risk factors, and provides important information for the risk factors. The forecast factors offer an interpretation of the level (dollar) and the slope (carry) factors derived by Lustig et al. (2011).

This chapter finds the risk price on the carry factor varies over time, and the global financial crisis has a large impact on this time variation. Menkhoff et al.'s (2012a) FX volatility innovation is a main driver of changes in the risk price of the carry factor. When FX market uncertainty rises, all investors unwind their carry positions simultaneously, and hence carry returns decline. The commodity price and the market liquidity forecast variables also have substantial impact during the crisis. Liquidity plays an important role only when it dries up significantly. This finding could be explained by liquidity spirals during the crisis, as suggested by Brunnermeier and Pedersen (2009). Importantly, the empirical results present evidence that time variations of risk factors dominate time variations of betas in generating small pricing errors. The weak support for time varying betas implies that investors overreact to changes in economic states, since investors know carry trades contain crash risk. Finally, time variation in risk prices suggests that predictability of carry trades is attributed to changes in the risk prices.

Chapter 6

Conclusion

This thesis discussed and implemented empirical factor models for currency carry trades. Sorting currency portfolios by interest rate differentials was beneficial since currency specific noise was averaged out. Many studies provide empirical evidence that this investment strategy provided a positive average return (e.g. Christiansen et al., 2011; Lustig and Verdelhan, 2011; Menkhoff et al. 2012a; Baksi and Panayotov 2013).

The previous literature has proposed several currency and non-currency risk factors to account for cross-sectional return differences across carry portfolios. Today, many financial market participants invest across asset classes and implement various investment strategies. Motivated by these points, Chapter 2 investigated information that is common to currency and non-currency factors. In terms of currency information, currency carry, FX volatility, long-run FX volatility, FX skewness were employed. In terms of non-currency information, global stock market return, downside global stock market return, TED spread, and durable and nondurable consumption growth were used. All these factors were standardized using the mimicking portfolio approach. The common factor was extracted by the PCA approach and this was adopted for stock and bond market forecast (Ludvigson and Ng, 2007, 2009)

The empirical results in Chapter 2 showed that the extracted common factor outperforms other widely used risk factors in terms of R^2, root mean squared pricing errors and pricing error test. This suggested that each risk factor contained noise since investors could not observe the true risk, and therefore the common factor was more robust to the noise. Orthogonalized factors were also adopted to explore whether the common factor found sufficient information from each original risk factor. The orthogonalized factors did not contain additional information in terms of explaining currency carry return, suggesting that the PCA was successful in extracting substantial information. The common factor approach was more useful in the all country portfolios than in the developed country portfolios. This implied that emerging currencies are not integrated with the world financial market. This, in turn, might be related to a lack of liquidity and a lack of openness in their financial markets.

Further, Chapter 2 looked at what the most substantial information contributing to the common factor was. The results presented empirical evidence that FX volatility and the downside world stock market return both play important roles. This suggested that both the FX market and stock market information were related to carry trades. Importantly, the correlation of these two variables was not large; this means that summarising information was a useful approach. Although stock market and currency carry risks somewhat overlapped, the empirical results implied that there exists heterogeneity. One of the possible explanations for this was that the financial institutions which invested in stock and currency markets did not completely overlap. Interestingly, the carry factor which was directly calculated from the currency portfolios did not have a large marginal R^2. Moreover, this chapter focused on the impact of excluding the dollar factor. When the dollar factor was excluded, the R^2 in the time series regressions showed that the common factor was more associated with the high interest rate currency portfolio than with the low interest rate currency portfolio. This demonstrated the common information was linked to risky currencies. This was rational because these currencies would be sensitive to FX and stock market crashes.

Chapter 3 sought to identify a new risk factor for currency carry trades. The investigation presented in this chapter tested whether commodity prices acted as risk factors for carry trades. This investigation takes into account commonalities within certain types of commodities as well as heterogeneities across commodity types. Following Moench et al. (2013), the dynamic hierarchical factor model was estimated. The results obtained in Chapter 3 implied that the commodity factors related to agricultural material goods and metals could price carry portfolios. The exploration also looked at whether the aggregate commodity common factor had relevant information for carry returns, while the empirical results did not support that idea. This implied that commodity heterogeneous information was critical for carry trade returns. Further, the common factor between commodity prices and other macro-finance variables was obtained, but this was not successful in pricing currency portfolios. This suggested that a simple PCA approach could not extract relevant information from the macro-finance data and that incorporating prior information relating to the data categories was useful for extracting the common factor.

Furthermore, Chapter 3 explored the information content of the agricultural material and metal factors. The empirical results presented that the agricultural material factor was related to emerging currencies and the metal factor was related to developed countries' currencies. Both factors were correlated with the carry factor. The carry factor was derived by a data driven approach, and hence investigation of the information content was important. These commodity factors contain different information from that the stock and FX market factors contain because they remained statistically significant after including the stock and FX market factors.

Parameter stability was another interesting question. Chapter 4 adopted conditional factor models and tested whether alphas and factor betas varied over time. This chapter used the daily data set as proposed by Lewellen and Nagel (2006), and it extracted information of changes in economic states. Further, alphas and betas were obtained by the nonparametric method as in Ang and Kristensen (2012). This approach provided smooth changes in alphas and betas, and determined the optimal window sizes. This chapter showed the statistically significant alphas, which were not observed using a conventional estimation approach. The constancy test presented evidence both alphas and betas vary over time.

Chapter 4 investigated what the main driving force for these changes was. In addition to macroeconomic variables, the analysis in this chapter employed several liquidity values such as the TED spread, the global FX market bid ask spread and Corwin and Schultz (2012) liquidity measures. The short term rate in the U.S. was related to the change in the alpha of the low interest rate currency portfolio, while the term spread played an important role in that of the high interest rate currency portfolio. The alpha in the low (high) interest rate currency portfolio was high (low) during recessions, while this pattern became weak once the FX volatility factor was controlled for. This suggested that just the average dollar factor alone was not enough to model the time series behaviours of currency portfolio returns. This point was interesting since the previous studies have stated that the dollar factor was the most important one in the time series context. The changes in the dollar factor beta and the FX volatility beta were driven by different mechanisms. For the dollar factor beta, a high short term rate and IP grow led to the high dollar factor beta in the high interest rate currency portfolio. However, the Term spread was positively, and the TED spread negatively, related to the FX volatility beta.

Time variation in risk prices was a cause of smaller pricing errors in the factor models. In Chapter 5, time-varying betas and risk price models were constructed and the driving forces behind the fluctuations in risk prices were investigated. This chapter found that market liquidity was negatively related to the risk price in the dollar factor. High FX market volatility led to a low risk price in the carry factor. The average risk price in the dollar factor was close to zero, and this has been reported in the literature, but this chapter found that the risk price during the global financial crisis was negative. Moreover, although the average risk price in the carry factor was positive, it fell to negative during the crisis. In addition to FX market volatility, the commodity price return, and market liquidity were driving forces in that period. The robustness test implied that without the crisis, the risk price time variation was small.

Furthermore, this chapter compared the time variation of risk prices with that of betas, in terms of pricing error impacts. The empirical results demonstrated that the time-varying risk prices played an important role in generating smaller pricing errors in the carry pricing model. This chapter also found the time-varying price estimation method proposed by Adrian et al. (2015) generate smaller pricing errors than traditional rolling regression approaches.

This thesis provides an important message for currency investors in terms of risk management. For instance, it showed that they need to monitor both stock and currency market risks and the time-varying betas imply a requirement to adjust portfolio risk levels based upon a business cycle. Another point worth mentioning is that the common factor approach is a powerful method in mitigating the effects of estimated risk factor noises. In addition, this thesis also helps to resolve the question of whether the constant risk price assumption is plausible or not.

Appendix A

Appendix of Chapter 2

This material contains more details of the research on Chapter 2. It presents that the correlation table across risk factors, data definition and sources, estimated betas on other factors, the comparison result between the common and stock market factors, and other robustness test results.

A.1 Country List of Chapter 2

The dataset covers the same 48 countries considered by Menkhoff et al. (2012a): Australia, Austria, Belgium, Brazil, Bulgaria, Canada, Croatia, Cyprus, Hong Kong, Czech Republic, Denmark, Egypt, Euro area, Finland, France, Germany, Greece, Hungary, Iceland, India, Indonesia, Ireland, Israel, Italy, Japan, Kuwait, Malaysia, Mexico, Netherlands, New Zealand, Norway, the Philippines, Poland, Portugal, Russia, Saudi Arabia, Singapore, Slovakia, South Africa, South Korea, Spain, Sweden, Switzerland, Taiwan, Thailand, Ukraine, and the United Kingdom. Developed country portfolios include: Australia, Belgium, Canada, Denmark, Euro area, France, Germany, Italy, Japan, Netherlands, New Zealand, Norway, Sweden, Switzerland, and the United Kingdom.

TABLE A.1: Sources and Definition of Data

Series	Definition	Source
Spot exchange rate	Spot exchange rate with bid and ask spread	Datastream
Forward exchange rate	Forward exchange rate with bid and ask spread	Datastream
TED spread	3 Month or 90 day Rates and Yields: Interbank Rates for the United States - 3 Month Treasury Bill: Secondary Market Rate	FRB St. Louis
World stock market	MSCI World total return index (USD)	Datastream
Risk free rate	1 Month Treasury Bill	K. R. French webpage
Nondurable consumption (ND)	Personal Consumption Expenditures: Nondurable Goods	FRB St. Louis
Population (TP)	Total Population: All Ages including Armed Forces Overseas	FRB St. Louis
CPI nondurable ($CPIND$)	Consumer Price Index for All Urban Consumers: Nondurables	FRB St. Louis
Real nondurable consumption in per capita (NC)	$(ND/TP)/CPIND$. ND/TP and $CPIND$ transformed into indexes and 1959 January =100	
Durable consumption (D)	Personal Consumption Expenditures: Durable Goods	FRB St. Louis
CPI durable ($CPID$) ($CPID$)	Consumer Price Index for All Urban Consumers: Durables	FRB St. Louis
Real durable consumption in per capita (C)	$(D/TP)/CPID$. D/TP and $CPID$ are transformed into indexes and 1959 January =100	

Notes: The table shows the definitions of data series.

TABLE A.2: Correlation Matrix

Panel A: All countries								
	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
(b)	**-0.32**							
(c)	**-0.17**	0.05						
(d)	**-0.17**	**-0.80**	0.04					
(e)	-0.13	**0.15**	0.05	**0.23**				
(f)	**0.18**	**-0.25**	-0.12	**-0.22**	**-0.19**			
(g)	**0.18**	**-0.31**	-0.06	**-0.24**	**-0.21**	**0.87**		
(h)	-0.04	0.02	0.11	0.07	0.00	0.12	**0.14**	
(i)	0.04	0.02	-0.01	0.07	-0.09	0.03	0.09	**0.20**
Panel A: All countries								
	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
(b)	**-0.31**							
(c)	**-0.18**	0.06						
(d)	**-0.19**	**-0.78**	0.06					
(e)	**-0.17**	**0.14**	0.05	**0.29**				
(f)	**0.21**	**-0.34**	-0.11	**-0.25**	**-0.19**			
(g)	**0.18**	**-0.31**	-0.08	**-0.27**	**-0.21**	**0.87**		
(h)	0.00	0.01	0.12	0.07	0.00	0.12	**0.14**	
(i)	0.03	0.04	-0.01	0.07	-0.09	0.03	0.09	**0.20**

Notes: The table contains Pearson correlation coefficients for risk factors. (a)HML_{FX} denotes the return spread between high and low currency portfolios, (b)ΔVOL_{FX} denotes the global FX volatility innovations, (c)$SKEW_{FX}$ denotes the global FX skewness, (d)$\Delta LVOL_{FX}$ denotes the long-run global FX volatility innovations, (e)ΔTED denotes the TED spread innovations, (f)$Wmkt$ denotes the excess return of the world stock market, (g)$DWmkt$ denotes the downside excess return of the world stock market, (h)ΔNC denotes the U.S. nondurable consumption growth, and (i)ΔC denotes the U.S. durable consumption growth. The sample period is from November 1983 to December 2013. The bold font indicates significance at the 1% level.

TABLE A.3: Factor Betas

Panel A: HML_{FX}

Portfolio	α	DOL	HML_{FX}	adj-R^2
P1	0.04	1.02***	-0.44***	0.92
	(0.04)	(0.02)	(0.03)	
P2	-0.10*	0.99***	-0.22***	0.87
	(0.05)	(0.03)	(0.03)	
P3	0.01	1.00***	-0.06**	0.90
	(0.05)	(0.02)	(0.03)	
P4	0.08	0.95***	0.07**	0.86
	(0.05)	(0.03)	(0.03)	
P5	-0.06	1.03***	0.08**	0.85
	(0.05)	(0.03)	(0.03)	
P6	0.04	1.02***	0.56***	0.94
	(0.04)	(0.02)	(0.03)	

Panel B: ΔVOL_{FX}

Portfolio	α	DOL	ΔVOL_{FX}	adj-R^2
P1	0.05*	1.17***	0.32***	0.97
	(0.03)	(0.01)	(0.01)	
P2	-0.11**	1.06***	0.13***	0.87
	(0.05)	(0.03)	(0.02)	
P3	0.00	1.01***	0.03*	0.90
	(0.05)	(0.02)	(0.02)	
P4	0.04	0.89***	-0.11***	0.88
	(0.05)	(0.03)	(0.02)	
P5	-0.09*	0.97***	-0.11***	0.87
	(0.05)	(0.03)	(0.02)	
65	0.11*	0.90***	-0.26***	0.85
	(0.06)	(0.03)	(0.02)	

Panel C: $Wmkt$

Portfolio	α	DOL	$Wmkt$	adj-R^2
P1	-0.06	1.36***	-0.48***	0.82
	(0.07)	(0.06)	(0.06)	
P2	-0.09*	1.37***	-0.50***	0.88
	(0.05)	(0.05)	(0.06)	
P3	0.08**	1.40***	-0.52***	0.94
	(0.04)	(0.04)	(0.04)	
P4	0.01	0.55***	0.51***	0.90
	(0.04)	(0.06)	(0.07)	
P5	-0.03	1.01***	0.03	0.85
	(0.06)	(0.07)	(0.06)	
P6	0.09	0.31***	0.96***	0.86
	(0.06)	(0.07)	(0.09)	

Notes: See the next page

Factor Betas (cont.)

Panel A: $DWmkt$

Portfolio	α	DOL	$DWmkt$	adj-R^2
P1	-0.01	1.38***	-1.15***	0.86
	(0.06)	(0.04)	(0.08)	
P2	-0.09*	1.25***	-0.79***	0.88
	(0.05)	(0.04)	(0.09)	
P3	0.06	1.22***	-0.66***	0.92
	(0.04)	(0.03)	(0.08)	
P4	-0.02	0.62***	0.97***	0.92
	(0.04)	(0.04)	(0.10)	
P5	-0.04	0.99***	0.13	0.85
	(0.05)	(0.05)	(0.11)	
P6	0.09	0.54***	1.50***	0.85
	(0.06)	(0.06)	(0.15)	

Notes: This table displays asset pricing results from time series regressions of excess returns of carry trade portfolios on a constant (α), the dollar risk (DOL) and the other factors using equation (2.1). We use the high minus low currency portfolios (HML_{FX}), global FX volatility innovations (ΔVOL_{FX}), world stock market excess return ($Wmkt$), and downside world stock market excess return ($DWmkt$). The test assets are six all country currency portfolios. The standard errors are reported in parentheses ($\cdot$) and obtained by the Newey and West (1987) procedure with optimal lag selection according to Andrews (1991). The adjusted R^2 are also reported. Asterisk *,**, and *** indicate significance at the 10%, 5% and 1% levels, respectively. The sample period is from November 1983 to December 2013.

TABLE A.4: Orthogonalized Common and Stock Market Factors

	(1)	(2)
DOL	0.18	0.18
	(0.12)	(0.12)
F	0.12***	
	(0.03)	
$Wmkt^{Orth}$	-0.02	
	(0.06)	
$Wmkt$		0.37***
		(0.11)
F^{Orth}		0.04***
		(0.02)
R^2	0.91	0.91
RMSE	0.05	0.05
χ^2	6.50*	6.50*
[p-value]	[0.09]	[0.09]

Notes: This table presents comparison results between the common factor F and the stock market factor. $Orth$ indicates the factor is orthogonalized with respect to the comparative factor. These cross-section regression results are estimated by equation (2.2). $Wmkt$ is the world stock market excess return. Shanken (1992) standard error are reported in parentheses $(\cdot)$. The null hypothesis of the χ^2 test is that there are no pricing errors. p-values are reported in square brackets $[\cdot]$. Asterisk *,**, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

TABLE A.5: Asset Pricing: Robustness

Panel A: Non-mimicking portfolio

All countries	DOL	f	RMSE	Developed countries	DOL	f	RMSE
λ	0.18	0.47***	0.05	λ	0.19	0.27***	0.09
	(0.12)	(0.12)			(0.13)	(0.10)	
R^2	0.88			R^2	0.60		
χ^2	6.17			χ^2	7.85**		
[p-value]	[0.19]			[p-value]	[0.05]		

Panel B: Carry and momentum portfolios

All countries	DOL	F	RMSE	Developed countries	DOL	F	RMSE
λ	0.18	0.11***	0.10	λ	0.18	0.09***	0.08
	(0.12)	(0.03)			(0.13)	(0.03)	
R^2	0.45			R^2	0.54		
χ^2	21.39**			χ^2	14.05*		
[p-value]	[0.02]			[p-value]	[0.08]		

Panel C: Individual currencies

All countries	DOL	F	RMSE	Developed countries	DOL	F	RMSE
λ	0.30**	0.12***	1.60	λ	0.24*	0.08*	1.32
	(0.13)	(0.05)			(0.14)	(0.04)	
R^2	0.30			R^2	0.32		

Panel D: Including global FX bid-ask spread innovations

All countries	DOL	F	RMSE	Developed countries	DOL	F	RMSE
λ	0.18	0.12***	0.06	λ	0.19	0.08***	0.09
	(0.12)	(0.03)			(0.13)	(0.03)	
R^2	0.87			R^2	0.60		
χ^2	7.61			χ^2	8.21**		
[p-value]	[0.11]			[p-value]	[0.04]		

Notes: See the next page

Asset Pricing: Robustness (cont.)

Panel E: Including short-run global FX volatility innovations

All countries				Developed countries			
	DOL	F	RMSE		DOL	F	RMSE
λ	0.18	0.12***	0.05	λ	0.19	0.08***	0.09
	(0.12)	(0.03)			(0.13)	(0.03)	
R^2	0.88			R^2	0.60		
χ^2	7.12			χ^2	8.23**		
[p-value]	[0.13]			[p-value]	[0.04]		

Panel F: Including global FX skewness innovations

All countries				Developed countries			
	DOL	F	RMSE		DOL	F	RMSE
λ	0.18	0.12***	0.05	λ	0.19	0.08***	0.09
	(0.12)	(0.03)			(0.13)	(0.03)	
R^2	0.88			R^2	0.61		
χ^2	6.84			χ^2	8.05**		
[p-value]	[0.14]			[p-value]	[0.05]		

Notes: This table displays cross-sectional pricing results of the linear factor model. The coefficient of factor risk premium λ in equation (2.2) is estimated by the procedure of Fama and MacBeth (1973). The dollar risk (DOL) and the common factors (F) are employed. Panel A uses the common factor (f) directly, not constructing the factor mimicking portfolio. Panel B adopt six (five) carry currency portfolios and six (five) momentum currency portfolios as test assets. Panel C employs individual currency excess returns as test assets. Panel D includes the basic nine risk factors and global FX bid-ask spread innovations, Panel E contains short-run global FX volatility innovations, and Panel F includes global FX skewness innovations. Shanken (1992) standard errors are reported in parentheses $(\cdot)$. The R^2 is a measure of fit between the sample mean of excess return and the predicted mean return. The RMSE is the root of mean-squared error and is reported in percentage points. The χ^2 test statistics of pricing errors are reported and the null hypothesis is that there is no pricing error. p-values are reported in square brackets $[\cdot]$. Asterisk *,**, and *** indicate significance at the 10%, 5% and 1% level, respectively. The sample period is from November 1983 to December 2013.

Appendix B

Appendix of Chapter 3

B.1 Uncovered Interest Parity

A carry trade is an investment strategy exploiting the empirical failure of Uncoverd Interest rate Parity (UIP). The failure of UIP is often observed in many currencies and is known as the forward premium puzzle. Lewis (1995) and Engel (1996) provide reviews of this puzzle. The currency excess return is written as:

$$r_{t+1} \approx i_t^* - i_t - \big(E_t s_{t+1} - s_t\big). \tag{B.1}$$

If the interest rate differential is positive (i.e., $i_t^* - i_t > 0$) and the USD depreciates against the foreign currency (i.e., $E_t s_{t+1} - s_t < 0$), the excess return will be positive. It will also be positive if the USD appreciates against the foreign currency and this appreciation does not offset the interest rate differential.

B.2 Generalized Method of Moments

In the chapter this study uses the Fama-MacBeth approach with Shanken standad errors following Burnside (2011). However, this study could also estimate the empirical asset pricing model using the generalized method of moments (GMM) proposed by Hansen (1982). As in Menkhoff et al. (2012a), this chapter uses the first stage of the GMM procedure which has the identity weight matrix. Following Cochrane (2005) and Burnside (2011), the moment conditions are:

$$\big[1 - b'(h_t - \mu)\big] r_t = 0 \tag{B.2}$$

$$h_t - \mu = 0 \tag{B.3}$$

$$vec\big((h_t - \mu)(h_t - \mu)'\big) - vec(\Sigma_h) = 0. \tag{B.4}$$

The first condition (B.2) is an N-dimensional vector that ensures the currency excess return satisfies the Euler equation.[1] equation (B.3) is an l-dimensional vector, indicating factor means μ are estimated values. The third condition (B.4) is an $l(l+1)/2$ dimensional vector and measures the estimation uncertainty of the factor covariance matrix. These conditions account for estimation uncertainty, since the factor means and the covariance matrix are estimated values. This study computes heteroskedasticity consistent standard errors as in Burnside (2011).

B.3 Data Treatment

This study pre-treats the spot and forward rate dataset by following the same methodology used by Darvas (2009) and Cenedese et al. (2014). This

[1] N is the number of the portfolios and l is the number of the factors.

involves using the previous day's observation if an observation exhibits any of the following: bid and ask rates are equal; the spread of the forward exchange rate is less than the spread of the spot exchange rate;[2] the daily spot rate changes but the daily forward rate stays constant and vice versa.

B.4 Commodity Exporting and Importing Countries

Following Ready et al. (2016), the commodity exporting countries include Australia (AUS), Canada (CAN), New Zealand (NZL), and Norway (NOR), and the commodity importing countries include the Euro (EUR), Germany (DEU), Japan (JPN), Sweden (SWE), and Switzerland (CHE). These two categories are based on the level of net exports in basic goods and net imports in finished goods.

B.5 Country-level Asset Pricing

This study adopts a country-level asset pricing model as a robustness check. Lustig et al. (2011), and Ahmed and Valente (2015) argue that the country-level model can deal with the data-snooping biases mentioned by Lo and MacKinlay (1990), and the information problems presented by Ang et al. (2010).[3]

Following the Fama and MacBeth (1973) procedure, this study runs the first-stage time series regressions. The excess return $r_{i,t}$ of currency i is regressed on DOL, factors estimated by DHFM, and a constant. This study then

[2]Although some currencies in forward markets may have enough liquidity and smaller spreads than those in spot markets, the dataset contains many emerging currencies, and this study simply follows this rule to standardize the data cleaning method.

[3]Lo and MacKinlay (1990) present evidence that finding a portfolio construction idea and testing it on the same dataset, leads to a data snooping bias. The bias may be serious when we use the portfolio approach. Ang et al. (2010) provide evidence that a risk premium depends upon the cross-sectional distribution of beta and idiosyncratic volatility. If we use portfolios, we lose some information of the beta distribution.

runs the following second-stage cross-sectional regression:

$$r_{i,t} = \lambda_{DOL,t}\beta_{i,t}^{DOL} + \lambda_{h,t}\beta_{i,t}^{h} + \epsilon_t \tag{B.5}$$

where $\lambda_{j,t}$ is the risk premium and $j = DOL$ or h, and $\beta_{i,t}^{j}$ is estimated by the first stage regression. This study estimates this cross-sectional model for each t and conducts statistical inference using mean λ_j and variance $\sigma^2(\lambda_j)$ as in Cochrane (2005):

$$\lambda_j = \frac{1}{T}\sum_{t=1}^{T}\lambda_{j,t}, \quad \sigma^2(\lambda_j) = \frac{1}{T^2}\sum_{t=1}^{T}(\lambda_{j,t} - \lambda_j)^2. \tag{B.6}$$

Similar to Lustig et al. (2011), this study uses the Newey and West (1987) procedure to correct for autocorrelations.

B.6 Country List of Chapter 3

The dataset covers the same 37 countries considered by Lustig et al. (2011): Australia, Austria, Belgium, Canada, Hong Kong, Czech Republic, Denmark, Euro area, Finland, France, Germany, Greece, Hungary, India, Indonesia, Ireland, Italy, Japan, Kuwait, Malaysia, Mexico, Netherlands, New Zealand, Norway, the Philippines, Poland, Portugal, Saudi Arabia, Singapore, South Africa, South Korea, Spain, Sweden, Switzerland, Taiwan, Thailand, and the United Kingdom. Developed country portfolios include: Australia, Belgium, Canada, Denmark, Euro area, France, Germany, Italy, Japan, Netherlands, New Zealand, Norway, Sweden, Switzerland, and the United Kingdom. Emerging country portfolios are constructed from the other 22 currencies.

TABLE B.1: Data and Model Structure

Block	Subblock	N
$B-COM$	$SB-FOO$	11
$B-COM$	$SB-AGR$	6
$B-COM$	$SB-MET$	6
$B-COM$	$SB-OIL$	3
$B-FIN$	$SB-STO$	6
$B-FIN$	$SB-INT$	15
$B-FIN$	$SB-MON$	13
$B-ECO$	$SB-INC$	9
$B-ECO$	$SB-PRO$	14
$B-ECO$	$SB-EMP$	25
$B-ECO$	$SB-HOU$	10
$B-ECO$	$SB-PRI$	14

Notes: This table summarizes the block structure of the four-level Dynamic Hierarchical Factor Model. N is the number of series in each subblock. There are three blocks (B): commodity price (COM), finance (FIN) and real economy (ECO). The commodity block has four subblocks (SB): food prices (FOO), agricultural material prices (AGR), metals (MET), and oil (OIL). The finance block has three subblocks (SB): stock market (STO), interest rate (INT), and money (MON). The real economy block has five subblocks: income and consumption (INC), production (PRO), employment (EMP), house (HOU), and price (PRI).

TABLE B.2: Cross-sectional Asset Pricing: Commodity and Finance Subblocks without Bid Ask Spreads

Panel A: Commodity Block				
	(1)	(2)	(3)	(4)
	λ	λ	λ	λ
DOL	0.24	0.24	0.24	0.25
	(0.12)	(0.12)	(0.12)	(0.12)
$SB-AGR$	0.63***			
	(0.17)			
$SB-MET$		0.73***		
		(0.24)		
$SB-FOO$			1.37*	
			(0.70)	
$SB-OIL$				0.78
				(0.93)
R^2	0.90	0.87	0.73	0.09
RMSE	0.08	0.09	0.14	0.25
χ^2	2.84	3.55	2.20	27.72***
[p-value]	[0.58]	[0.47]	[0.70]	[0.00]

Panel B: Finance Block			
	(5)	(6)	(7)
	λ	λ	λ
DOL	0.23	0.24	0.24
	(0.12)	(0.12)	(0.12)
$SB-STO$	0.51***		
	(0.14)		
$SB-INT$		-3.93	
		(2.71)	
$SB-MON$			-0.48***
			(0.17)
R^2	0.86	0.50	0.31
RMSE	0.10	0.18	0.22
χ^2	5.82	2.02	13.62**
[p-value]	[0.21]	[0.73]	[0.01]

Notes: This table reports cross-sectional pricing results of the cross-sectional pricing results of the linear factor model based on the commodity prices or financial risk factors. The test assets are excess returns of six carry trade portfolios without trading costs. The coefficient of factor risk premium λ in equation (3.6) is estimated by the procedure of Fama and MacBeth (1973). Abbreviations of the factor variables are reported in the first column. DOL is the dollar risk factor. $SB-FOO$ is food prices, $SB-AGR$ is agricultural material prices, $SB-MET$ is metal prices, $SB-OIL$ is oil prices, $SB-STO$ is stock market, $SB-INT$ is interest rate, and $SB-MON$ is money factors estimated by the Dynamic Hierarchical Factor Model. Shanken (1992) standard errors are reported in parentheses. The R^2 is a measure of fit between the sample mean and the predicted mean returns. The RMSE is the root of mean-squared error and is reported in percentage points. The χ^2 test statistics of pricing errors are reported and the null hypothesis is that there is no pricing error. p-values are reported in square brackets. *,**, and *** indicate significance at the 10%, 5% and 1% levels, respectively. The sample period is from February 1983 to December 2013.

TABLE B.3: Cross-sectional Asset Pricing: GMM

	(1)		(2)		(3)	
	b	λ	b	λ	b	λ
DOL	-0.02	0.15	-0.06	0.15	-0.23	0.17
	(0.04)	(0.12)	(0.05)	(0.12)	(0.03)	(0.14)
$SB-AGR$	1.94*	0.30**				
	(1.05)	(0.14)				
$SB-MET$			2.08*	0.31**		
			(1.14)	(0.15)		
$SB-STO$					1.97*	0.24**
					(1.09)	(0.12)
R^2	0.57		0.53		0.85	
RMSE	0.10		0.11		0.06	
χ^2	6.24		8.27*		4.60	
[p-value]	[0.18]		[0.08]		[0.33]	

Notes: This table reports cross-sectional pricing results of the linear factor model based on the commodity prices or financial risk factors. The test assets are excess returns of six carry trade portfolios. Coefficients of SDF parameter b and factor risk premium λ are estimated by GMM, and the first stage GMM results are reported. Abbreviations of the factor variables are reported in the first column. DOL is the dollar risk factor. $SB-AGR$ is the agricultural material prices, $SB-MET$ is the metal, and $SB-STO$ is the stock market factors estimated by the Dynamic Hierarchical Factor Model. GMM-VARHAC standard errors are reported in parentheses. The R^2 is a measure of fit between the sample mean and the predicted mean returns. The RMSE is the root of mean-squared error and is reported in percentage points. The χ^2 test statistics of pricing errors are reported and the null hypothesis is that there is no pricing error. p-values are reported in square brackets. *,**, and *** indicate significance at the 10%, 5% and 1% levels, respectively. The sample period is from February 1983 to December 2013.

TABLE B.4: Cross-sectional Asset Pricing: Commodity Index

	(1) λ	(2) λ	(3) λ	(4) λ	(5) λ
DOL	0.16	0.16	0.15	0.15	0.16
	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)
CRB	3.94				
	(2.60)				
$IMF-AGR$		0.81			
		(1.03)			
$IMF-MET$			4.03**	-0.65	
			(1.95)	(3.08)	
$IMF-MET^{orth}$					-3.57
					(3.01)
$SB-MET$					0.33*
					(0.18)
$SB-MET^{orth}$				0.38*	
				(0.22)	
R^2	0.38	0.10	0.43	0.61	0.61
RMSE	0.13	0.15	0.12	0.10	0.10
χ^2	7.75	19.61***	12.32**	5.35	5.35
[p-value]	[0.10]	[0.00]	[0.02]	[0.15]	[0.15]

Notes: This table reports cross-sectional pricing results of the linear factor model based on the commodity prices factors. The test assets are excess returns of six carry trade portfolios without trading costs. The coefficient of factor risk premium λ in equation (3.6) is estimated by the procedure of Fama and MacBeth (1973). Abbreviations of the factor variables are reported in the first column. DOL is the dollar risk factor. CRB is the CRB Raw industrial material subkinex return as in Bakshi and Pnayotov (2013). $IMF-AGR$ is the IMF agricultural material index, $IMF-MET$ is the IMF metal index, and both are computed as real returns. $IMF-MET^{orth}$ is the orthogonalized IMF metal index real return. $SB-MET$ is the metal factor estimated by the Dynamic Hierarchical Factor Model and $SB-MET^{orth}$ is the orthogonalized metal factor. The R^2 is a measure of fit between the sample mean and the predicted mean returns. The RMSE is the root of mean-squared error and is reported in percentage points.The χ^2 test statistics of pricing errors are reported and the null hypothesis is that there is no pricing error. p-values are reported in square brackets. *,**, and *** indicate significance at the 10%, 5% and 1% levels, respectively. The sample period is from February 1983 to December 2013.

TABLE B.5: Country-level Asset Pricing

	(1)	(2)	(3)
	λ	λ	λ
DOL	0.27**	0.24**	0.26**
	(0.13)	(0.13)	(0.13)
$SB-AGR$	0.18**		
	(0.09)		
$SB-MET$		0.18**	
		(0.07)	
$SB-STO$			0.08*
			(0.04)
R^2	0.25	0.28	0.29
RMSE	1.58	1.54	1.52

Notes: This table reports cross-sectional pricing results using individual currencies. The factor risk premium λ is obtained by equations (B.5) and (B.6). Abbreviations of the factor variables are reported in the first column. DOL is the dollar risk factor. $SB-AGR$ is the agricultural material prices, $SB-MET$ is the metal, and $SB-STO$ is the stock market factors estimated by the Dynamic Hierarchical Factor Model. The standard errors are reported in parentheses and obtained by the Newey and West (1987) procedure with optimal lag selection according to Andrews (1991). The R^2 and RMSE is average of time series. The RMSE is the root mean-squared error and is reported in percentage points. *,**, and *** indicate significance at the 10%, 5% and 1% levels, respectively. The sample period is from February 1983 to December 2013.

TABLE B.6: Time Series Regression with HML_{FX}

	Panel A: Stock Market Risk				
	$SB-AGR$	$SB-MET$	ΔVOL_{World}		adjR^2
(1)	1.34***		-1.23**		0.09
	(0.46)		(0.51)		
(2)		1.17***	-1.18***		0.08
		(0.41)	(0.43)		
	Panel B: CRB index				
	$SB-AGR$	$SB-MET$	CRB	CRB^{orth}	adjR^2
(3)	1.38***		0.96		0.05
	(0.46)		(5.32)		
(4)		1.25***	1.31		0.04
		(0.46)	(4.84)		
(5)	1.40***			0.96	0.05
	(0.41)			(5.32)	
(6)		1.28***		1.31	0.04
		(0.43)		(4.84)	
	Panel C: Orthogonalized IMF index				
	$SB-AGR$	$SB-MET$	$IMF-AGR^{orth}$	$IMF-MET^{orth}$	adjR^2
(7)	1.40***		-0.02		0.05
	(0.47)		(0.05)		
(8)		1.28***		-0.01	0.04
		(0.43)		(0.04)	
	Panel D: IMF index				
	$SB-AGR^{orth}$	$SB-MET^{orth}$	$IMF-AGR$	$IMF-MET$	adjR^2
(9)	1.46***		0.07		0.05
	(0.46)		(0.05)		
(10)		1.35***		0.08**	0.04
		(0.49)		(0.03)	

Notes: This table shows results for time series regressions of HML_{FX} on a constant (α) and factors. HML_{FX} is the high minus low currency portfolios as in Lustig et al. (2011). $SB-AGR$ is the agricultural material prices, $SB-MET$ is the metals factors estimated by the Dynamic Hierarchical Factor Model. $SB-AGR^{orth}$ is the orthogonalized agricultural material prices, $SB-MET^{orth}$ is the orthogonalized metals factors. ΔVOL_{world} is the global stock market volatility innovations using MSCI World index. CRB is the CRB Raw industrial material subkinex return as in Bakshi and Panayotov (2013), CRB^{orth} is the the orthogonalized CRB Raw industrial material subkinex return. $IMF-AGR$ is the IMF agricultural material index, $IMF-MET$ is the IMF metals index, and both are computed as a real return. $IMF-AGR^{orth}$ is the IMF agricultural material index, $IMF-MET^{orth}$ is the IMF metals index, and both are computed as a orthogonalized real return. The estimation results of constant term are not reported. The standard errors are reported in parentheses and obtained by the Newey and West (1987) procedure with optimal lag selection according to Andrews (1991). The adjusted R^2 are also reported. *,**, and *** indicate significance at the 10%, 5% and 1% levels, respectively. The sample period is from February 1983 and December 2013.

TABLE B.7: Data Sources, Transformation, and Definition

Number	Short name	Tran	Source	Description
Real Economy($B-ECO$)				
Income and Consumption ($SB-INC$)				
1	PI	lnFD	DS	Personal Income Account, SA, United States Dollar
2	PCE	FD	FRB	Real personal consumption expenditures, Percent Change from Preceding Period, SA
3	PCE	lnSD	FRB	Personal Consumption Expenditures: Chain-type Price Index,SA
4	PCE:D	lnSD	FRB	Personal Consumption Expenditures: Durable Goods,SA
5	PCE:ND	lnSD	FRB	Personal Consumption Expenditures: Nondurable Goods,SA
6	PCE:S	lnSD	FRB	Personal Consumption Expenditures: Services,SA
7	AHE	lnSD	DS	United States, Average Hourly Earnings of Production and Nonsupervisory Employees, SA, Total
8	AHE:const	lnSD	DS	United States, Average Hourly Earnings of Production and Nonsupervisory Employees, SA, Construction
9	AHE:mfg	lnSD	DS	United States, Average Hourly Earnings of Production and Nonsupervisory Employees, SA, Manufacturing
Production ($SB-PRO$)				
10	IP:total	lnFD	DS	Production, Overall, Total, Volume, SA, Index, 2007 = 100
11	IP:FP	lnFD	DS	Production, Market Groups, Final Products Total, Volume, SA, Index, 2007 = 100
12	IP:CG	lnFD	DS	Production, Market Groups, Consumer Goods Total, Volume, SA, Index, 2007 = 100
13	IP:CDG	lnFD	DS	Production, Market Groups, Consumer Durable Goods Total, Volume, SA, Index, 2007 = 100
14	IP:CNDG	lnFD	DS	Production, Market Groups, Consumer Nondurable Goods Total, Volume, SA, Index, 2007 = 100
15	IP:EB	lnFD	DS	Production, Market Groups, Equipment, Business Total, Volume, SA, Index, 2007 = 100
16	IP:MT	lnFD	DS	Production, Market Groups, Materials Total, Volume, SA, Index, 2007 = 100
17	IP:MF	lnFD	DS	Production, Manufacturing, Overall, Total (SIC), Volume, SA, Index, 2007 = 100
18	IP:RU	lnFD	DS	Production, Market Groups, Consumer Nondurable, Energy, Residential Utilities, Volume, SA, Index, 2007 = 100
19	IP:F	lnFD	DS	Production, Market Groups, Consumer Nondurable, Energy, Fuels, Volume, SA, Index, 2007 = 100
20	ISM:M	level	FRB	ISM Manufacturing: Production Index,SA
21	CU	FD	FRB	Capacity Utilization: Total Industry, Percent of of Capacity, Monthly, Seasonally Adjusted
22	PMI	level	FRB	ISM Manufacturing: PMI Composite Index,SA
23	ISM:NO	level	FRB	ISM Manufacturing: New Orders Index,SA
Employment ($SB-EMP$)				
24	EMP:total	lnFD	DS	Employment, Overall, Total (Civilian, Household Survey), SA
25	UER:total	FD	DS	Unemployed, Rate, Total, SA
26	U:mean	FD	DS	Unemployed, by Duration, Average in Weeks, SA
27	U:5wks	lnFD	DS	Unemployed, by Duration, For Less Than 5 Weeks, SA
28	U:5-14wks	lnFD	DS	Unemployed, by Duration, For 5-14 Weeks, SA
29	U:15wks	lnFD	DS	Unemployed, by Duration, For 15 Weeks or More, SA
30	U:15-26wks	lnFD	DS	Unemployed, by Duration, For 15-26 Weeks, SA
31	U:27wks	lnFD	DS	Unemployed, by Duration, For 27 Weeks or More, SA
32	UI:claims	lnFD	FRB	Initial Claims, Number, Monthly, Seasonally Adjusted
33	AWPR	lnFD	FRB	Indexes of Aggregate Weekly Payrolls of Production and Nonsupervisory Employees,SA, Index, 2002 = 100
34	NFP:goods	lnFD	DS	Non-Farm Payrolls, Goods-Producing, SA, Index, 2002 = 100
35	NFP:ML	lnFD	DS	Non-Farm Payrolls, Mining and Logging, SA, Index, 2002 = 100
36	NFP:C	lnFD	DS	Non-Farm Payrolls, Construction, SA, Index, 2002 = 100
37	NFP:Mf	lnFD	DS	Non-Farm Payrolls, Manufacturing, SA, Index, 2002 = 100
38	NFP:DG	lnFD	DS	Non-Farm Payrolls, Durable Goods, SA, Index, 2002 = 100
39	NFP:NDG	lnFD	DS	Non-Farm Payrolls, Nondurable Goods, SA, Index, 2002 = 100
40	NFP:BS	lnFD	DS	Non-Farm Payrolls, Professional and Business Services, SA, Index, 2002 = 100
41	NFP:TU	lnFD	DS	Non-Farm Payrolls, Trade, Transportation, and Utilities, SA, Index, 2002 = 100
42	NFP:WT	lnFD	DS	Non-Farm Payrolls,Wholesale Trade, SA, Index, 2002 = 100
43	NFP:RT	lnFD	DS	Non-Farm Payrolls, Retail Trade, SA, Index, 2002 = 100

Continued: Data Sources, Transformation, and Definition

Number	Short name	Tran	Source	Description
44	NFP:FA	lnFD	DS	Non-Farm Payrolls, Financial Activities, SA, Index, 2002 = 100
45	NFP:GP	level	DS	Non-Farm Payroll, Goods Producing Industries Total, SA
46	AWO	FD	DS	Average Weekly Overtime of Production Workers, Manufacturing, SA
47	AWH	level	DS	Average Weekly Hours of Production Workers, Goods-Producing, Industries Manufacturing, Total, SA
48	ISM	level	FRB	ISM Manufacturing: Employment Index,SA
House ($SB-HOU$)				
49	HS:total	ln	DS	Housing Starts, Total, AR, SA
50	HS:NE	ln	DS	Housing Starts, North East Region, AR, SA
51	HS:NE	ln	DS	Housing Starts, Midwest Region, AR, SA
52	HS:S	ln	DS	Housing Starts, South Region, AR, SA
53	HS:W	ln	DS	Housing Starts, West Region, AR, SA
54	BP:total	ln	DS	Building Permits, Total, AR, SA
55	BP:NE	ln	DS	Building Permits, by Region, Northeast, AR, SA
56	BP:MW	ln	DS	Building Permits, by Region, Midwest, AR, SA
57	BP:S	ln	DS	Building Permits, by Region, South, AR, SA
58	BP:W	ln	DS	Building Permits, by Region, West, AR, SA
Price($SB-PRI$)				
59	PPI:FG	lnSD	FRB	Producer Price Index: Finished Goods,SA
60	PPI:FCG	lnSD	FRB	Producer Price Index: Finished Consumer Goods,SA
61	PPI:IM	lnSD	FRB	Producer Price Index: Intermediate Materials: Supplies and Components,SA
62	PPI:CM	lnSD	FRB	Producer Price Index: Crude Materials for Further Processing,SA
63	CPI:all	lnSD	FRB	Consumer Price Index for All Urban Consumers: All Items,SA
64	CPI:A	lnSD	FRB	Consumer Price Index for All Urban Consumers: Apparel,SA
65	CPI:T	lnSD	FRB	Consumer Price Index for All Urban Consumers: Transportation,SA
66	CPI:MC	lnSD	FRB	Consumer Price Index for All Urban Consumers: Medical care,SA
67	CPI:C	lnSD	FRB	Consumer Price Index for All Urban Consumers: Commodities,SA
68	CPI:D	lnSD	FRB	Consumer Price Index for All Urban Consumers: Durables,SA
69	CPI:S	lnSD	FRB	Consumer Price Index for All Urban Consumers: Services,SA
70	CPI:LF	lnSD	FRB	Consumer Price Index for All Urban Consumers: All Items Less Food,SA
71	CPI:LS	lnSD	FRB	Consumer Price Index for All Urban Consumers: All items less shelter,SA
72	CPI:LMC	lnSD	FRB	Consumer Price Index for All Urban Consumers: All items less medical care,SA
Finance($B-FIN$)				
Stock Market($SB-STO$)				
73	SP500	lnFD	DS	Standard and Poor's 500 Composite
74	SPID	lnFD	DS	Standard and Poor's Industrial
75	MKT	level	French	Fama and French Mkt-RF factor
76	SMB	level	French	Fama and French SMB factor
77	HML	level	French	Fama and French HML factor
78	MOM	level	French	Momentum factor
Interest Rate($SB-INT$)				
79	FF	FD	FRB	Effective Federal Funds Rate
80	3MTB	FD	DS	United States Treasury Bill SEC Market 3 Month
81	6MTB	FD	DS	United States Treasury Bill SEC Market 6 Month
82	1YTB	FD	DS	United States Treasury Constant Maturity 1 Year
83	5YTB	FD	DS	United States Treasury Benchmark Bond 5 Years
84	10YTB	FD	DS	United States Treasury Benchmark Bond 10 Years
85	Aaa	FD	FRB	Moody's Seasoned Aaa Corporate Bond Yield
86	Baa	FD	FRB	Moody's Seasoned Baa Corporate Bond Yield
87	3MTB-FF	level	-	3MTB-FF
88	6MTB-FF	level	-	6MTB-FF

Continued: Data Sources, Transformation, and Definition

Number	Short name	Tran	Source	Description
89	1YTB-FF	level	-	1YTB-FF
90	5YTB-FF	level	-	5YTB-FF
91	10YTB-FF	level	-	10YTB-FF
92	Aaa-FF	level	-	Aaa-FF
93	Baa-FF	level	-	Baa-FF
Money($SB-MOT$)				
94	M1	lnSD	DS	Money Supply Money Supply M1, SA, United States Dollar
95	M2	lnSD	DS	Money Supply Money Supply M2, SA, United States Dollar
96	M3	lnSD	FRB	M3 for the United States,SA
97	MB	lnSD	FRB	St. Louis Adjusted Monetary Base,SA
98	BDI	lnSD	FRB	Total Borrowings of Depository Institutions from the Federal Reserve
99	RDI	FD	FRB	Reserves Of Depository Institutions, Nonborrowed
100	CIL	lnSD	FRB	Commercial and Industrial Loans, All Commercial Banks,SA
101	NCC	level	FRB	Nonrevolving Consumer Credit Owned and Securitized, Flow,SA
102	REER	lnFD	FRB	Real Narrow Effective Exchange Rate for United States
103	FX:Swiss	lnFD	FRB	Switzerland / U.S. Foreign Exchange Rate
104	FX:Japan	lnFD	FRB	Japan / U.S. Foreign Exchange Rate
105	FX:UK	lnFD	FRB	U.S. / U.K. Foreign Exchange Rate
106	FX:Canada	lnFD	FRB	Canada / U.S. Foreign Exchange Rate
Commodity($B-COM$)				
Food($SB-MOT$)				
107	Wheat	lnFD	IMF	Wheat
108	Maize	lnFD	IMF	Maize (corn)
109	Rice	lnFD	IMF	Rice
110	Palm oil	lnFD	IMF	Palm oil
111	Beef	lnFD	IMF	Beef
112	Lamb	lnFD	IMF	Lamb
113	Sugar	lnFD	IMF	Sugar
114	Bananas	lnFD	IMF	Bananas
115	Coffee	lnFD	IMF	Coffee
116	Cocoa beans	lnFD	IMF	Cocoa beans
117	Tea	lnFD	IMF	Tea
Agricultural Material($SB-AGR$)				
118	Sawnwood	lnFD	WB	Sawnwood (Malaysia)
119	Cotton	lnFD	IMF	Cotton
120	Wool	lnFD	IMF	Wool
121	Rubber	lnFD	IMF	Rubber
122	Hides	lnFD	IMF	Hides
123	Tobacco	lnFD	WB	Tobacco (any origin)
Metal($SB-MET$)				
124	Copper	lnFD	IMF	Copper
125	Aluminum	lnFD	IMF	Aluminum
126	Tin	lnFD	IMF	Tin
127	Zinc	lnFD	IMF	Zinc
128	Lead	lnFD	IMF	Lead
129	Silver	lnFD	WB	Silver
Oil($SB-OIL$)				
130	Oil:DB	lnFD	IMF	Crude Oil (petroleum), Dated Brent, light blend 38 API, fob U.K., USD per barrel
131	Oil:Dubai	lnFD	IMF	Oil; Dubai, medium, Fateh 32 API, fob Dubai Crude Oil (petroleum), Dubai Fateh Fateh 32 API, USD per barrel
132	Oil:WTI	lnFD	IMF	Crude Oil (petroleum), West Texas Intermediate 40 API, Midland Texas, USD per barrel

Notes: This Table shows the short name of each series, the transformation applied to the series, data source and a brief data description. In the transformation column, level denotes level of the series, ln denotes logarithm, FD and SD denote the first and second difference, and lnFD and lnSD denote the first and second difference of the logarithm. In the source column, DB denotes Datastream, FRB denotes the Federal Reserve Bank St.Louis, IMF denotes the IMF commodity price table, WB denotes the World Bank commodity price data.The data period is from January 1983 to December 2013.

Appendix C

Appendix of Chapter 4

This material provides additional results which are not reported in the main text. Section A presents the constant coefficient test procedure and Section B shows the bandwidth estimation procedure. Tables and Figures present the results of another specification that includes high minus low interest rate currency portfolios, HML_{FX}, using the subsample that contains only developed countries.

C.1 F Statistic

The constant coefficient $\hat{\alpha}_i$ is obtained as in Ang and Kristensen (2009), and Kristensen (2012). This study treats α_i as known and consider the following problem:

$$\begin{aligned} \hat{\beta}_{i,\tau} &= \arg\min_{(\beta_i)} \sum_{t=1}^{T} K_{h_i T}(t-\tau)(ret_{i,t} - \alpha_i - \beta_i' f_t)^2 \\ &= \hat{m}_{R_i,\tau} - \hat{m}_{1,\tau}\alpha_i \end{aligned} \tag{C.1}$$

where

$$\hat{m}_{R_{i,\tau}} = \left[\sum_{t=1}^{T} K_{h_iT}(t-\tau) f_t f_t^{'}\right]^{-1} \left[\sum_{t=1}^{T} K_{h_iT}(t-\tau) f_t ret_{i,t}^{'}\right]$$

$$\hat{m}_{1,\tau} = \left[\sum_{t=1}^{T} K_{h_iT}(t-\tau) f_t f_t^{'}\right]^{-1} \left[\sum_{t=1}^{T} K_{h_iT}(t-\tau) f_t 1^{'}\right].$$

To obtain the constant $\hat{\alpha}_i$, the estimated $\hat{\beta}_{i,t}$ is substituted into the weighted least-squares criterion $Q_T(\alpha_i)$:

$$Q_T(\alpha_i) = \sum_{t=1}^{T} \hat{\Omega}_{ii,t}^{-1} \left[ret_{i,t} - \alpha_i - \hat{\beta}_{i,t}^{'} f_t\right]^2. \qquad \text{(C.2)}$$

α_i, which minimizes the criterion, is obtained by the following least squares problem:

$$\hat{\alpha}_i = \left[\sum_{t=1}^{T} \hat{\Omega}_{ii,t}^{-1} \hat{X}_{1,t} \hat{X}_{1,t}^{'}\right]^{-1} \left[\sum_{t=1}^{T} \hat{\Omega}_{ii,t}^{-1} \hat{X}_{1,t} \hat{R}_t^{'}\right] \qquad \text{(C.3)}$$

where $\hat{X}_{1,t} = 1 - \hat{m}_{,\tau} f_t$ and $\hat{R}_t = ret_{i,t} - \hat{m}_{R_{i,\tau}} f_t$.

C.2 Bandwidth Estimation

A bandwidth is obtained by the plug-in method as in Ang and Kristensen (2009), and Kristensen (2012). This method is a two step approach and the first-pass bandwidth is estimated by imposing assumptions on unknown variables. Assuming that $\Lambda_t = \Lambda$ and $\Omega_t = \Omega$ are constant, and $\beta_{i,t} = b_{0,i} + b_{1,i}t + \cdots + b_{p,i}t^p$ is a polynomial of order $p \geq 2$. $\tilde{\Lambda}$, $\tilde{\Omega}$, and $\tilde{\beta}_{i,t} = \tilde{b}_{0,i} + \tilde{b}_{1,i}t + \cdots + \tilde{b}_{p,i}t^p$ are estimated by parametric least squares. Following Ang and Kristensen (2012), this study chooses the polynomial order of degree 6. For each portfolio i, $\tilde{V}_i$

and $\tilde{B}_i$ are computed as:

$$\tilde{V}_i = \frac{\kappa_2}{T}\tilde{\Lambda}^{-1} \otimes \tilde{\Omega}, \quad \tilde{B}_i = \frac{1}{T}\sum_{t=1}^{T} ||\tilde{\beta}_{i,t}^{(2)}||^2$$

where $\kappa_2 = 0.2821$ for the Gaussian kernel, $||\cdot||$ is the Euclidean norm and $\tilde{\beta}_{i,t}^{(2)} = 2\tilde{b}_{2,i} + 6\tilde{b}_{3,i}t + \cdots + p(p-1)\tilde{b}_{p,i}t^{p-2}$. The first-pass bandwidth, $\tilde{h}_i$, is obtained using these estimates:

$$\tilde{h}_i = \left[\frac{\tilde{V}_i}{\tilde{B}_i}\right]^{1/5} \times T^{-1/5} \tag{C.4}$$

Using $\tilde{h}_i$ in equation (C.4), $\hat{\alpha}_{i,t}$, $\hat{\beta}_{i,t}$, $\hat{\Lambda}_t$, and $\hat{\Omega}_t$ are estimated by equations (4.2) and (4.3) in the main text. Then, $\hat{V}_i$ and $\hat{B}_i$ are computed as:

$$\hat{V}_i = \frac{\kappa_2}{T}\hat{\Lambda}_t^{-1} \otimes \hat{\Omega}_t, \quad \hat{B}_i = \frac{1}{T}\sum_{t=1}^{T} ||\hat{\beta}_{i,t}^{(2)}||^2.$$

Applying the same step of the first-pass, the second-pass bandwidth $\hat{h}_i$ is obtained as:

$$\hat{h}_i = \left[\frac{\hat{V}_i}{\hat{B}_i}\right]^{1/5} \times T^{-1/5}. \tag{C.5}$$

C.3 Country List

The dataset covers the following 38 countries: Australia, Austria, Brazil, Bulgaria, Canada, Croatia, Hong Kong, Czech Republic, Denmark, Euro area, France, Germany, Greece, Hungary, Iceland, India, Indonesia, Italy, Japan, Malaysia, Mexico, Netherlands, New Zealand, Norway, Poland, Russia, Singapore, Slovakia, South Africa, South Korea, Spain, Sweden, Switzerland, Taiwan, Thailand, Ukraine, and the United Kingdom. Developed country portfolios include: Australia, Belgium, Canada, Denmark, Euro area, France, Germany, Italy, Japan, Netherlands, New Zealand, Norway, Sweden, Switzerland, and the United Kingdom.

TABLE C.1: Long-run Alphas and Betas by Two Factor Model

Portfolio	Fraction	Months	$\hat{\alpha}_{LR}$	$\hat{\beta}_{DOL}$	$\hat{\beta}_{HMLFX}$
All countries					
Panel A: Long-run alphas and betas					
P1	0.065	41.6	0.096***	0.978***	-0.423***
			(0.020)	(0.005)	(0.004)
P2	0.082	53.0	-0.657***	1.005***	-0.103***
			(0.019)	(0.007)	(0.005)
P3	0.089	57.3	-0.217***	1.009***	-0.041***
			(0.027)	(0.007)	(0.005)
P4	0.069	44.6	0.717***	1.021***	-0.013**
			(0.040)	(0.010)	(0.007)
P5	0.065	41.6	0.096***	0.978***	0.577***
			(0.020)	(0.005)	(0.004)
Panel B: OLS alphas and betas					
P1			-0.294*	1.042***	-0.348***
			(0.154)	(0.027)	(0.031)
P2			-0.329***	0.890***	-0.171***
			(0.094)	(0.033)	(0.020)
P3			0.254***	0.952***	-0.123***
			(0.085)	(0.039)	(0.019)
P4			0.662***	1.073***	-0.010
			(0.190)	(0.057)	(0.028)
P5			-0.294*	1.042***	0.652***
			(0.154)	(0.027)	(0.031)
Developed countries					
Panel C: Developed countries and two factor model					
P1	0.089	57.1	0.402***	0.978***	-0.597***
			(0.017)	(0.013)	(0.004)
P2	0.061	39.0	-0.542***	1.010***	0.024***
			(0.019)	(0.008)	(0.005)
P3	0.089	57.4	-0.206***	1.074***	0.069***
			(0.021)	(0.007)	(0.005)
P4	0.067	43.0	-0.038	0.963***	0.100***
			(0.030)	(0.009)	(0.006)
P5	0.089	57.1	0.402***	0.978***	0.403***
			(0.017)	(0.009)	(0.004)
Panel D: OLS alphas and betas					
P1			0.516***	1.043***	-0.626***
			(0.121)	(0.027)	(0.037)
P2			-0.649***	0.859***	0.000
			(0.074)	(0.043)	(0.022)
P3			-0.362***	0.999***	0.093***
			(0.067)	(0.042)	(0.021)
P4			-0.020***	1.056***	0.159
			(0.144)	(0.080)	(0.041)
P5			0.516***	1.043***	0.374***
			(0.121)	(0.027)	(0.037)

Notes: This table presents the conditional bandwidths, long-run alphas, and betas on the dollar (DOL) and the high minus low interest rate currency portfolios (HML_{FX}). The conditional bandwidth is reported in fractions of the entire sample and obtained as in Kristensen (2012). They are transformed to monthly equivalent units by multiplying $320 \times 1.96/0.975$, where there are 320 months in the sample. The long-run alpha and betas are obtained by equation (4.4) and the standard errors are reported in parentheses and obtained by equation (4.5). The long-run alphas are annualized to multiply 252. Panels B and D show the results of OLS and the standard errors are reported in parentheses and obtained by the Newey and West (1987) procedure with optimal lag selection according to Andrews (1991). Asterisk *,**, and *** indicate significance at the 10%, 5% and 1% levels, respectively.

TABLE C.2: Tests of Constant Alphas and Betas

Portfolio	F-statistics α_{LR}	β_{DOLFX}	β_{HMLFX}	Critical Value 95%	99%
Panel A: All countries and two factor model					
P1	8833***	1435***	12654***	91	97
P2	3723***	11532***	2359***	73	79
P3	1544***	6497***	2186***	68	73
P4	10300***	11003***	4710***	86	92
P5	8833***	1435***	12654***	91	97
Panel B: Developed countries and two factor model					
P1	2747***	182***	1324***	68	73
P2	1147***	1275***	2080***	96	102
P3	1173***	2076***	1891***	68	71
P4	11206***	14114***	3164***	88	94
P5	2747***	182***	1324***	68	73

Notes: This table presents the test of constancy of the alphas and betas on the dollar (DOL) and the high minus low interest rate currency portfolios (HML_{FX}). F statistic is computed by equation (4.9) and 95% and 99% critical values are reported. Asterisk *,**, and *** indicate significance at the 10%, 5% and 1% levels, respectively.

TABLE C.3: Explaining Conditional Alphas Estimated by Developed Country One Factor Model

Panel A: Portfolio 1	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$SHORT$	-0.25***								-0.24***
	(0.06)								(0.09)
$TERM$		0.31***							-0.01
		(0.11)							(0.10)
IP			-0.05***						0.00
			(0.02)						(0.03)
VOL_{FX}				1.76***					0.79
				(0.44)					(0.61)
TED					-0.34				-0.08
					(0.32)				(0.31)
$DMKT$						-0.01			0.02
						(0.02)			(0.02)
BAS							-5.39		2.57
							(5.55)		(4.48)
CS								0.33***	0.02
								(0.11)	(0.21)
$adjR^2$	0.54	0.27	0.09	0.14	0.03	0.00	0.03	0.12	0.56

Panel B: Portfolio 5	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$SHORT$	0.11***								0.16***
	(0.04)								(0.06)
$TERM$		-0.14**							0.08
		(0.06)							(0.09)
IP			0.03***						0.00
			(0.01)						(0.01)
VOL_{FX}				-0.83***					0.20
				(0.30)					(0.45)
TED					0.15				0.04
					(0.16)				(0.12)
$DMKT$						0.02**			0.01
						(0.01)			(0.01)
BAS							-0.29		-6.54*
							(3.52)		(3.94)
CS								-0.17***	-0.07
								(0.06)	(0.12)
$adjR^2$	0.34	0.16	0.08	0.10	0.02	0.01	0.00	0.09	0.43

Notes: This table shows the results of monthly conditional alphas of P1 and P5 are regressed on market state variables. These alphas are estimated by the one factor model which has the dollar (DOL). The portfolios are constructed by developed country currencies. The monthly data is obtained as the end of the month daily conditional alphas. $SHORT$ is the three month T-Bill yield, $TERM$ is the difference between 10 year and three month T-Bill yields, IP is the industrial production growth, VOL_{FX} is the global FX volatility, TED is the TED spread, $DMKT$ is the downside stock market excess return, BAS is the global FX bid-ask-spreads, and CS is the Corwin and Schultz liquidity measure. The standard errors are reported in parentheses and obtained by the Newey and West (1987) procedure with optimal lag selection according to Andrews (1991). Asterisk *,**, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

TABLE C.4: Explaining Conditional Betas on DOL Estimated by Developed Country One Factor Model

Panel A: Portfolio 1	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$SHORT$	0.02								0.00
	(0.02)								(0.04)
$TERM$		-0.03							-0.02
		(0.03)							(0.04)
IP			0.02***						0.02***
			(0.01)						(0.01)
VOL_{FX}				-0.28***					-0.44***
				(0.10)					(0.15)
TED					-0.06				-0.06
					(0.09)				(0.05)
$DMKT$						0.01			0.00
						(0.00)			(0.00)
BAS							0.88		1.13
							(1.86)		(2.05)
CS								-0.03	0.12**
								(0.03)	(0.06)
$adjR^2$	0.03	0.02	0.16	0.04	0.01	0.00	0.01	0.01	0.18

Panel B: Portfolio 5	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$SHORT$	-0.05***								-0.08***
	(0.01)								(0.01)
$TERM$		0.07*							-0.04
		(0.03)							(0.03)
IP			-0.02***						-0.01**
			(0.01)						(0.00)
VOL_{FX}				0.47***					0.19*
				(0.11)					(0.11)
TED					0.01				0.10***
					(0.09)				(0.04)
$DMKT$						-0.01**			0.00
						(0.00)			(0.00)
BAS							0.89		4.03***
							(1.95)		(0.82)
CS								0.08***	-0.05
								(0.02)	(0.04)
$adjR^2$	0.33	0.18	0.16	0.16	0.00	0.01	0.01	0.10	0.55

Notes: This table shows the results of monthly conditional betas on DOL of P1 and P5 are regressed on market state variables. These betas are estimated by the one factor model which has the dollar (DOL). The portfolios are constructed by developed country currencies. The monthly data is obtained as the end of the month daily conditional betas. $SHORT$ is the three month T-Bill yield, $TERM$ is the difference between 10 year and three month T-Bill yields, IP is the industrial production growth, VOL_{FX} is the global FX volatility, TED is the TED spread, $DMKT$ is the downside stock market excess return, BAS is the global FX bid-ask-spreads, and CS is the Corwin and Schultz liquidity measure. The standard errors are reported in parentheses and obtained by the Newey and West (1987) procedure with optimal lag selection according to Andrews (1991). Asterisk *,**, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

TABLE C.5: Explaining Conditional Alphas Estimated by Developed Country Two Factor Model

Panel A: Portfolio 1	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$SHORT$	-0.09***								-0.08***
	(0.02)								(0.02)
$TERM$		0.07							-0.02
		(0.05)							(0.02)
IP			-0.03***						-0.01
			(0.01)						(0.01)
VOL_{FX}				0.67***					0.07
				(0.17)					(0.23)
TED					0.03				0.08
					(0.10)				(0.08)
$DMKT$						0.00			0.00
						(0.00)			(0.00)
BAS							-5.20***		-2.10
							(1.87)		(1.32)
CS								0.14***	0.02
								(0.03)	(0.06)
$adjR^2$	0.46	0.09	0.15	0.14	0.00	0.00	0.20	0.15	0.56

Panel B: Portfolio 5	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$SHORT$	0.02**								0.01
	(0.01)								(0.01)
$TERM$		0.01							0.01
		(0.02)							(0.01)
IP			0.00						0.00
			(0.00)						(0.00)
VOL_{FX}				-0.07					-0.13
				(0.07)					(0.11)
TED					-0.01				0.00
					(0.04)				(0.02)
$DMKT$						0.00			0.00
						(0.00)			(0.00)
BAS							3.30***		.2.84***
							(0.60)		(0.56)
CS								-0.01***	0.03
								(0.01)	(0.03)
$adjR^2$	0.16	0.00	0.02	0.01	0.00	0.00	0.50	0.01	0.53

Notes: This table shows the results of monthly conditional alphas of P1 and P5 are regressed on market state variables. These alphas are estimated by the two factor model which has the dollar (DOL) and the global FX volatility innovations (ΔVOL_{FX}). The portfolios are constructed by developed country currencies. The monthly data is obtained as the end of the month daily conditional alphas. $SHORT$ is the three month T-Bill yield, $TERM$ is the difference between 10 year and three month T-Bill yields, IP is the industrial production growth, VOL_{FX} is the global FX volatility, TED is the TED spread, $DMKT$ is the downside stock market excess return, BAS is the global FX bid-ask-spreads, and CS is the Corwin and Schultz liquidity measure. The standard errors are reported in parentheses and obtained by the Newey and West (1987) procedure with optimal lag selection according to Andrews (1991). Asterisk *,**, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

TABLE C.6: Explaining Conditional Betas on DOL Estimated by Developed Country Two Factor Model

Panel A: Portfolio 1									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$SHORT$	-0.01								-0.06
	(0.01)								(0.04)
$TERM$		0.05							0.00
		(0.03)							(0.04)
IP			0.01*						0.02**
			(0.01)						(0.01)
VOL_{FX}				0.01					0.03
				(0.07)					(0.21)
TED					-0.08				0.06
					(0.08)				(0.06)
$DMKT$						0.00			0.01**
						(0.00)			(0.00)
BAS							4.44***		6.10***
							(1.48)		(1.26)
CS								-0.01	0.00
								(0.02)	(0.07)
$adjR^2$	0.00	0.07	0.05	0.00	0.01	0.00	0.19	0.00	0.36
Panel B: Portfolio 5									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$SHORT$	-0.02**								-0.03***
	(0.01)								(0.01)
$TERM$		0.00							-0.03***
		(0.02)							(0.01)
IP			-0.01***						0.00
			(0.00)						(0.00)
VOL_{FX}				0.18***					-0.05
				(0.05)					(0.06)
TED					0.03				0.02
					(0.03)				(0.03)
$DMKT$						0.00			0.00
						(0.00)			(0.00)
BAS							-1.41***		-0.10
							(0.48)		(0.39)
CS								0.04***	0.02
								(0.01)	(0.02)
$adjR^2$	0.23	0.00	0.10	0.10	0.01	0.00	0.15	0.14	0.42

Notes: This table shows the results of monthly conditional betas on DOL of P1 and P5 are regressed on market state variables. These betas are estimated by the two factor model which has the dollar (DOL) and the global FX volatility innovations (ΔVOL_{FX}). The portfolios are constructed by developed country currencies. The monthly data is obtained as the end of the month daily conditional betas. $SHORT$ is the three month T-Bill yield, $TERM$ is the difference between 10 year and three month T-Bill yields, IP is the industrial production growth, VOL_{FX} is the global FX volatility, TED is the TED spread, $DMKT$ is the downside stock market excess return, BAS is the global FX bid-ask-spreads, CS is the Corwin and Schultz liquidity measure. The standard errors are reported in parentheses and obtained by the Newey and West (1987) procedure with optimal lag selection according to Andrews (1991). Asterisk *,**, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

TABLE C.7: Explaining Conditional Betas on ΔVOL_{FX} Estimated by Developed Country Two Factor Model

Panel A: Portfolio 1	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$SHORT$	-0.14*							-0.07
	(0.07)							(0.05)
$TERM$		0.17***						-0.12
		(0.06)						(0.08)
IP			-0.10***					-0.01
			(0.03)					(0.02)
TED				0.72**				-0.11
				(0.42)				(0.13)
$DMKT$					-0.05***			-0.02
					(0.02)			(0.01)
BAS						3.39		15.88***
						(4.81)		(3.62)
CS							0.65***	0.00
							(0.12)	(0.07)
$adjR^2$	0.05	0.02	0.13	0.04	0.03	0.00	0.16	0.38

Panel B: Portfolio 5	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$SHORT$	0.03							-0.20
	(0.02)							(0.16)
$TERM$		0.04						-0.15
		(0.07)						(0.18)
IP			0.00					-0.05
			(0.01)					(0.05)
TED				-0.09				0.50
				(0.14)				(0.47)
$DMKT$					-0.01			-0.06*
					(0.01)			(0.03)
BAS						12.37***		13.01**
						(3.36)		(6.30)
CS							0.02*	0.19
							(0.06)	(0.33)
$adjR^2$	0.01	0.01	0.00	0.00	0.00	0.34	0.00	0.24

Notes: This table shows the monthly conditional betas on ΔVOL_{FX} of P1 and P5 are regressed on market state variables. These betas are estimated by the two factor model which has the dollar (DOL) and the global FX volatility innovations (ΔVOL_{FX}). The portfolios are constructed by developed country currencies. The monthly data is obtained as the end of the month daily conditional betas. $SHORT$ is the three month T-Bill yield, $TERM$ is the difference between 10 year and three month T-Bill yields, IP is the industrial production growth, VOL_{FX} is the global FX volatility, TED is the TED spread, $DMKT$ is the downside stock market excess return, BAS is the global FX bid-ask-spreads, and CS is the Corwin and Schultz liquidity measure. The standard errors are reported in parentheses and obtained by the Newey and West (1987) procedure with optimal lag selection according to Andrews (1991). Asterisk *,**, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

TABLE C.8: Explaining Conditional Alphas and Betas Estimated by All Country One Factor Model

Panel A: Portfolio 1	(1)	(2)	(3)	(4)	(5)	(6)
		LAR	GTS		LAR	GTS
	α	α	α	β_{DOL}	β_{DOL}	β_{DOL}
$SHORT$	-0.10**	-0.10**	-0.18***	0.09***	0.09***	0.08***
	(0.05)	(0.05)	(0.05)	(0.03)	(0.03)	(0.02)
$TERM$	0.16*	0.16		0.04	0.05	
	(0.10)	(0.10)		(0.04)	(0.03)	
IP	-0.03	-0.03		0.00		
	(0.02)	(0.02)		(0.01)		
VOL_{FX}	2.46***	2.44***	3.43***	0.31	0.23	0.27*
	(0.73)	(0.72)	(1.21)	(0.20)	(0.17)	(0.15)
TED	-0.11	-0.11		-0.17***	-0.18***	-0.21***
	(0.15)	(0.15)		(0.07)	(0.05)	(0.07)
$DMKT$	0.00			0.00	0.00	
	(0.01)			(0.01)	(0.00)	
BAS	-0.15	-0.12		-2.73***	-2.82***	-2.46***
	(3.27)	(3.23)		(1.12)	(0.95)	(0.91)
CS	-0.68**	-0.68**	-0.93**	-0.03		
	(0.28)	(0.27)	(0.36)	(0.08)		
$adjR^2$	0.55	0.55	0.49	0.34	0.34	0.32

Panel B: Portfolio 5	(1)	(2)	(3)	(4)	(5)	(6)
		LAR	GTS		LAR	GTS
	α	α	α	β_{DOL}	β_{DOL}	β_{DOL}
$SHORT$	-0.11	-0.11		-0.02	-0.02	
	(0.09)	(0.09)		(0.05)	(0.05)	
$TERM$	-0.49***	-0.49***	-0.39***	-0.02	-0.02	
	(0.15)	(0.15)	(0.10)	(0.06)	(0.06)	
IP	0.04	0.04		0.03	0.03	
	(0.03)	(0.03)		(0.02)	(0.02)	
VOL_{FX}	-4.78***	-4.78***	-5.56***	-1.39***	-1.39***	-1.92***
	(0.95)	(0.95)	(1.21)	(0.33)	(0.33)	(0.51)
TED	0.11	0.11		0.27	0.27	
	(0.34)	(0.34)		(0.18)	(0.18)	
$DMKT$	0.02	0.02		0.01	0.01	
	(0.02)	(0.02)		(0.01)	(0.01)	
BAS	7.11	7.11		4.00***	4.00***	3.84**
	(4.85)	(4.85)		(1.53)	(1.53)	(1.56)
CS	1.76***	1.76***	2.06***	0.24**	0.24**	0.37***
	(0.32)	(0.32)	(0.41)	(0.11)	(0.11)	(0.13)
$adjR^2$	0.55	0.55	0.51	0.26	0.26	0.20

This table shows the results of monthly conditional alphas and betas of P1 and P5 are regressed on market state variables. These alphas and betas are estimated by the one factor model which has the dollar (DOL). The portfolios are constructed by all country currencies. Least angle regressions (LAR) and general-to-specific approach (GTS) are used to specify the model. The standard errors are reported in parentheses and obtained by the Newey and West (1987) procedure with optimal lag selection according to Andrews (1991). Asterisk *,**, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

TABLE C.9: Explaining Conditional Alphas and Betas Estimated by Developed Country One Factor Model

Panel A: Portfolio 1						
	(1)	(2)	(3)	(4)	(5)	(6)
		LAR	GTS		LAR	GTS
	α	α	α	β_{DOL}	β_{DOL}	β_{DOL}
$SHORT$	-0.24***	-0.24***	-0.23***	0.00		
	(0.09)	(0.05)	(0.06)	(0.04)		
$TERM$	-0.01			-0.02	-0.02	
	(0.10)			(0.04)	(0.03)	
IP	0.00			0.02***	0.02***	0.02***
	(0.03)			(0.01)	(0.01)	(0.01)
VOL_{FX}	0.79	0.83**	0.64**	-0.44***	-0.44**	-0.44***
	(0.61)	(0.37)	(0.31)	(0.15)	(0.18)	(0.16)
TED	-0.08	-0.08		-0.06	-0.07	
	(0.31)	(0.29)		(0.05)	(0.05)	
$DMKT$	0.02	0.02		0.00		
	(0.02)	(0.02)		(0.00)		
BAS	2.57	2.36		1.13	0.99	
	(4.48)	(3.25)		(2.05)	(1.40)	
CS	0.02			0.12**	0.12**	0.10**
	(0.21)			(0.06)	(0.06)	(0.05)
$adjR^2$	0.56	0.57	0.56	0.18	0.19	0.18
Panel B: Portfolio 5						
	(1)	(2)	(3)	(4)	(5)	(6)
		LAR	GTS		LAR	GTS
	α	α	α	β_{DOL}	β_{DOL}	β_{DOL}
$SHORT$	0.16***	0.16***	0.13***	-0.08***	-0.08***	-0.06***
	(0.06)	(0.06)	(0.04)	(0.01)	(0.01)	(0.02)
$TERM$	0.08	0.08		-0.04	-0.04	
	(0.09)	(0.09)		(0.03)	(0.03)	
IP	0.00	0.00		-0.01**	-0.01**	-0.01**
	(0.01)	(0.01)		(0.00)	(0.00)	(0.00)
VOL_{FX}	0.20	0.20		0.19*	0.19*	
	(0.45)	(0.45)		(0.11)	(0.11)	
TED	0.04	0.04		0.10***	0.10***	0.10***
	(0.12)	(0.12)		(0.04)	(0.04)	(0.04)
$DMKT$	0.01	0.01		0.00	0.00	
	(0.01)	(0.01)		(0.00)	(0.00)	
BAS	-6.54*	-6.54*	-4.70**	4.03***	4.03***	3.12**
	(3.94)	(3.94)	(1.98)	(0.82)	(0.82)	(1.26)
CS	-0.07	-0.07		-0.05	-0.05	
	(0.12)	(0.12)		(0.04)	(0.04)	
$adjR^2$	0.43	0.43	0.40	0.55	0.55	0.52

This table shows the results of monthly conditional alphas and betas of P1 and P5 are regressed on market state variables. These alphas and betas are estimated by the one factor model which has the dollar (DOL). The portfolios are constructed by developed country currencies. Least angle regressions (LAR) and general-to-specific approach (GTS) are used to specify the model. The standard errors are reported in parentheses and obtained by the Newey and West (1987) procedure with optimal lag selection according to Andrews (1991). Asterisk *,**, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

TABLE C.10: Explaining Conditional Alphas and Betas Estimated by All Country Two Factor Model

Panel A: Portfolio 1						
	(1)	(2)	(3)	(4)	(5)	(6)
	LAR	GTS	LAR	GTS	LAR	GTS
	α	α	β_{DOL}	β_{DOL}	$\beta_{\Delta VOLFX}$	$\beta_{\Delta VOLFX}$
$SHORT$	-0.01		-0.01*		0.09	0.13***
	(0.01)		(0.01)		(0.06)	(0.05)
$TERM$	-0.01		0.01	0.02**	0.30***	0.33***
	(0.01)		(0.01)	(0.01)	(0.10)	(0.12)
IP	0.00		0.01**	0.00*	-0.01	
	(0.00)		(0.00)	(0.00)	(0.05)	
VOL_{FX}	0.15	0.29***	-0.14**	-0.21***		
	(0.10)	(0.08)	(0.07)	(0.06)		
TED	-0.08***	-0.09**	0.03		-0.43	-0.54***
	(0.02)	(0.04)	(0.02)		(0.27)	(0.18)
$DMKT$	0.00		0.00		-0.05**	-0.04*
	(0.00)		(0.00)		(0.02)	(0.02)
BAS	-0.35		1.63***	1.37***	1.42	
	(0.30)		(0.29)	(0.30)	(2.86)	
CS	0.01		-0.05**		-0.21*	
	(0.04)		(0.02)		(0.12)	
$adjR^2$	0.33	0.20	0.40	0.39	0.21	0.21

Panel B: Portfolio 5						
	(1)	(2)	(3)	(4)	(5)	(6)
	LAR	GTS	LAR	GTS	LAR	GTS
	α	α	β_{DOL}	β_{DOL}	$\beta_{\Delta VOLFX}$	$\beta_{\Delta VOLFX}$
$SHORT$	-0.03	-0.04**	0.02	0.04***	0.24	
	(0.02)	(0.02)	(0.02)	(0.02)	(0.24)	
$TERM$	0.03		-0.02		1.13***	0.91***
	(0.04)		(0.03)		(0.37)	(0.33)
IP	-0.01		0.02**	0.02***		
	(0.02)		(0.01)	(0.01)		
VOL_{FX}	0.54***	0.67***	-0.29			
	(0.20)	(0.19)	(0.22)			
TED	-0.30***	-0.31***	-0.03		-2.03***	-1.63***
	(0.05)	(0.06)	(0.11)		(0.51)	(0.53)
$DMKT$			0.01	0.01***	-0.10**	-0.11***
			(0.00)	(0.00)	(0.04)	(0.04)
BAS			1.55*			
			(0.90)			
CS					-0.51	-0.91**
					(0.46)	(0.38)
$adjR^2$	0.35	0.34	0.43	0.39	0.34	0.33

This table shows the results of monthly conditional alphas and betas of P1 and P5 are regressed on market state variables. These alphas and betas are estimated by the two factor model which has the dollar (DOL) and the global FX volatility innovations (ΔVOL_{FX}). The portfolios are constructed by all country currencies. Least angle regressions (LAR) and general-to-specific approach (GTS) are used to specify the model. The standard errors are reported in parentheses and obtained by the Newey and West (1987) procedure with optimal lag selection according to Andrews (1991). *,**, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

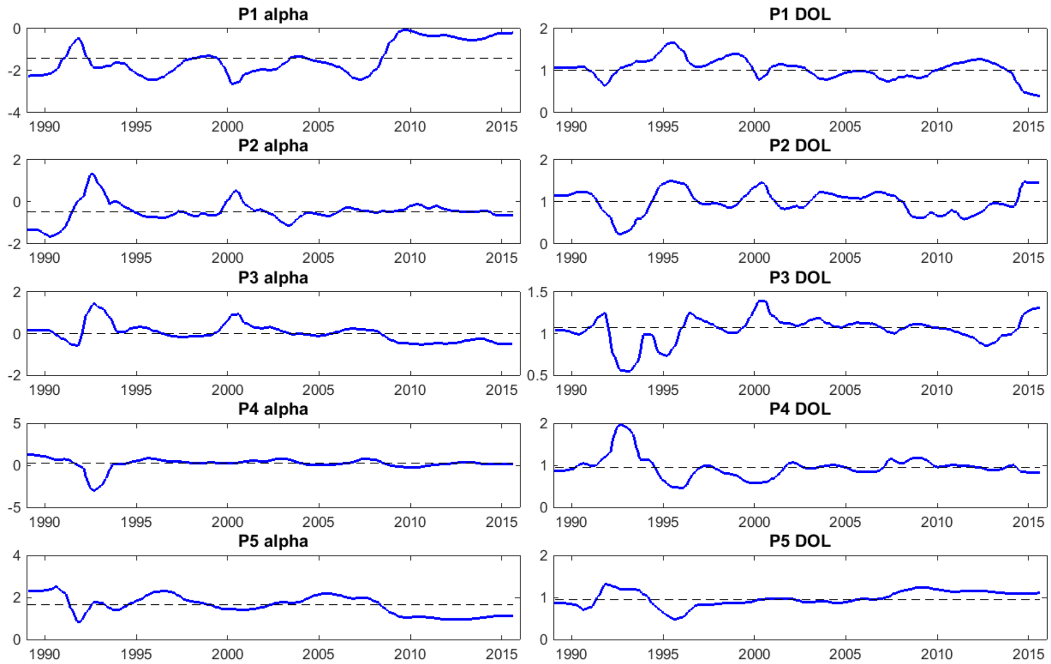
TABLE C.11: Explaining Conditional Alphas and Betas Estimated by Developed Country Two Factor Model

Panel A: Portfolio 1	(1)	(2)	(3)	(4)	(5)	(6)
	LAR	GTS	LAR	GTS	LAR	GTS
	α	α	β_{DOL}	β_{DOL}	$\beta_{\Delta VOLFX}$	$\beta_{\Delta VOLFX}$
$SHORT$	-0.08***	-0.08***	-0.05**	-0.05***	-0.07	
	(0.02)	(0.01)	(0.02)	(0.01)	(0.05)	
$TERM$	-0.02				-0.12	
	(0.02)				(0.08)	
IP	-0.01		0.02**	0.02**	-0.01	-0.09***
	(0.01)		(0.01)	(0.01)	(0.02)	(0.03)
VOL_{FX}	0.07		0.03			
	(0.23)		(0.14)			
TED	0.08	0.13	0.06		-0.11	
	(0.08)	(0.06)	(0.06)		(0.13)	
$DMKT$	0.00	-0.01*	0.01***		-0.02	-0.10***
	(0.00)	(0.00)	(0.00)		(0.01)	(0.03)
BAS	-2.10	-2.32**	6.00***	5.85***	15.88***	
	(1.32)	(1.05)	(0.66)	(0.51)	(3.62)	
CS	0.02				0.00	
	(0.06)				(0.07)	
$adjR^2$	0.56	0.54	0.36	0.36	0.38	0.17

Panel B: Portfolio 5	(1)	(2)	(3)	(4)	(5)	(6)
	LAR	GTS	LAR	GTS	LAR	GTS
	α	α	β_{DOL}	β_{DOL}	$\beta_{\Delta VOLFX}$	$\beta_{\Delta VOLFX}$
$SHORT$	0.01		-0.03***	-0.03***	-0.07	
	(0.01)		(0.01)	(0.01)	(0.05)	
$TERM$	0.01		-0.03***	-0.03***	-0.12	
	(0.01)		(0.01)	(0.01)	(0.08)	
IP	0.00		0.00	0.02***	-0.01	
	(0.00)		(0.00)	(0.01)	(0.02)	
VOL_{FX}	-0.14	-0.07**				
	(0.10)	(0.03)				
TED			0.01		-0.11	
			(0.03)		(0.15)	
$DMKT$			0.00		-0.02	
			(0.00)		(0.01)	
BAS	2.86***	3.31***	-0.13*		15.87***	12.37***
	(0.56)	(0.62)	(0.39)		(3.51)	(3.36)
CS	0.03		0.02	0.03***		
	(0.03)		(0.02)	(0.01)		
$adjR^2$	0.53	0.51	0.42	0.41	0.39	0.34

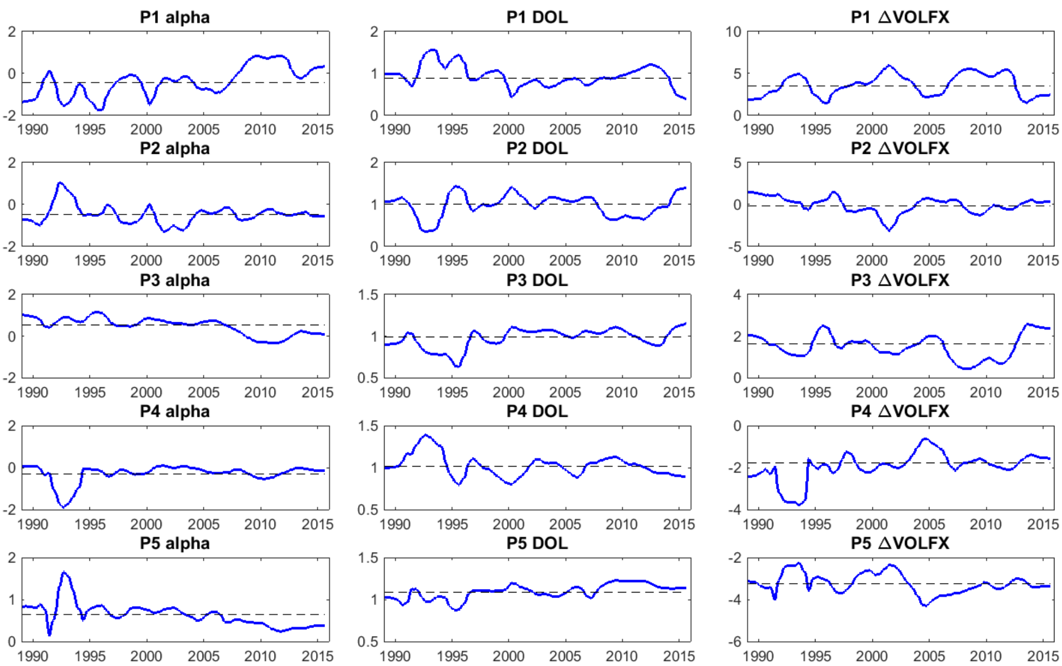
This table shows the results of monthly conditional alphas and betas of P1 and P5 are regressed on market state variables. These alphas and betas are estimated by the two factor model which has the dollar (DOL) and the global FX volatility innovations (ΔVOL_{FX}). The portfolios are constructed by developed country currencies. Least angle regressions (LAR) and general-to-specific approach (GTS) are used to specify the model. The standard errors are reported in parentheses and obtained by the Newey and West (1987) procedure with optimal lag selection according to Andrews (1991). Asterisk *,**, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

FIGURE C.1: Conditional alphas and betas of developed country one factor model



Notes:This figure provides plots of the estimated conditional short-run (thick line) and the average of long-run (dash line) alphas and betas of developed country portfolios. The one factor model includes the dollar (DOL).

FIGURE C.2: Conditional alphas and betas of developed country two factor model



Notes:This figure provides plots of the estimated conditional short-run (thick line) and the average of long-run (dash line) alphas and betas of developed country portfolios. The two factor model includes the dollar (DOL) and the global FX volatility innovations (ΔVOL_{FX})

Appendix D

Appendix of Chapter 5

This material provides additional results which are not reported in the main text. Section A shows estimation procedures for the constant beta and time-varying risk price model and the time-varying beta and risk price model. Section B explains the bandwidth estimation process using the time-varying beta and risk price model. Section C proposes another liquidity factor as a forecast factor based on bid-ask spreads. Tables and Figures present robustness.

D.1 Estimation Procedure

This section shows an estimation process of the constant beta and time-varying risk price model and the time-varying beta and risk price model as in Adrian et al. (2015). This chapter uses the following three steps for the constant beta and time-varying risk price model.

D.1.1 Constant Beta and Time-varying Risk Price Model Estimation

1. Using stack vectors, equation (5.3) is written as:

$$R = B\lambda_0 \iota_T' + B\Lambda_1 F_- + BU + E, \tag{D.1}$$

where R is the $N \times T$ carry return matrix, ι_T is a $T \times 1$ vector of ones, $F_{-} = [F_0 \dots F_T]$ is the $K_F \times T$ forecast factor matrix, U is the $K_C \times T$ innovations term matrix, which is extracted as the first K_c columns of V, where $V = [v_1 \dots v_T]$, and v_j is the innovation vector of the jth risk factor. E is the $N \times T$ pricing error matrix. B is the $N \times K_C$ factor beta matrix and $B = (\beta_1, \dots, \beta_N)'$ where β_j is the coefficient obtained by regressing the carry return vector of portfolio i on the innovation vector of the jth risk factor. There are two risk price matrices, and λ_0 is the $K_C \times 1$ and Λ_1 is the $K_C \times K_F$. In the first step, the VAR model in equation (5.4) is estimated and $\hat{\Sigma}_u = \hat{U}\hat{U}'/T$ and $\hat{\gamma}_{FF} = \tilde{F}_{-}\tilde{F}_{-}'/T$ are obtained.

2. Let $A_0 = B\lambda_0$ and $A_1 = B\Lambda_1$, and equation (D.1) can be written as:

$$R = A_0\iota_T' + A_1 F_{-} + BU + E. \tag{D.2}$$

Let $\hat{z}_t = (1, F_{t-1}', \hat{u}_t')$, $\hat{Z} = [\iota_T \; F_{-}' \; \hat{U}']'$, and $\hat{A} = R\hat{Z}'(\hat{Z}\hat{Z})^{-1}$ is estimated by equation (D.2). The heteroskedasticity robust standard error $\hat{\nu}_{rob}$ is obtained as:

$$\hat{\nu}_{rob} = T\left(\left(\hat{Z}\hat{Z}'\right)^{-1} \otimes I_N\right)\left(\sum_{t=1}^{T} \left(\hat{z}_t\hat{z}_t' \otimes \hat{e}_t\hat{e}_t'\right)\right)\left(\left(\hat{Z}\hat{Z}'\right)^{-1} \otimes I_N\right) \tag{D.3}$$

where $\hat{e}_t = R_t - \hat{A}\hat{z}_t$, I_N is the $N \times N$ identity matrix. This heteroskedasticity robust variance estimator is used in Table 5.1. .

3. The risk price parameters, $\hat{\lambda}_0$ and $\hat{\Lambda}_1$, are obtained as:

$$\hat{\lambda}_0 = (\hat{B}'\hat{B})^{-1}\hat{B}'\hat{A}_0, \; \hat{\Lambda}_1 = (\hat{B}'\hat{B})^{-1}\hat{B}'\hat{A}_1. \tag{D.4}$$

The heteroskedasticity robust standard error $\hat{\nu}_{\Lambda,ols}$ is obtained as:

$$\hat{\nu}_{\Lambda,ols} = \left(\hat{\gamma}_{FF}^{-1} \otimes \hat{\Sigma}_u\right) + \eta_\lambda\big(\hat{B}, \hat{\Lambda}\big)\hat{\nu}_{rob}\eta_\lambda\big(\hat{B}, \hat{\Lambda}\big)' \tag{D.5}$$

where $\eta_\lambda = \Bigg[\big(I_{(K_F+1)} \otimes (\hat{B}'\hat{B})^{-1}B' \quad -\big(\hat{\Lambda}' \otimes (\hat{B}'\hat{B})^{-1}\hat{B}'\big)\Bigg]$. This heteroskedasticity robust variance estimator is used for the constant beta and time-varying risk price model.

D.1.2 Time-varying Beta and Risk Price Model Estimation

For the time-varying beta and risk price model, the kernel estimation method proposed by Ang and Kristensen (2012) is employed in the steps 1 and 2.

1. Let $\Psi_t = (\mu_t \ \Phi_t)$ and the VAR model in equation (5.8) is estimated as:

$$\big[\hat{\Psi}_{t-1}\big]_i = \sum_{s=1}^{T} K_b\bigg(\frac{s-t}{T}\bigg) X_{i,s}\tilde{X}'_{s-1}\bigg(\sum_{s=1}^{T} K_b\bigg(\frac{s-t}{T}\bigg)\tilde{X}_{s-1}\tilde{X}'_{s-1}\bigg)^{-1} \tag{D.6}$$

where $b = b_i^{sr}$ is the short-run bandwidth as in Ang and Kristensen (2012), $X_{i,s}$ is the ith element of X_s and $\tilde{X}_{s-1} = (1, X'_{s-1})'$. Following Ang and Kristensen (2012), $K(x)$ is the Gaussian density as:

$$K(x) = \frac{1}{\sqrt{2\pi}} exp\bigg(-\frac{x^2}{2}\bigg) \tag{D.7}$$

The residual vector $\hat{v}_t$ is obtained as $\hat{v}_t = X_t - \hat{\Psi}_{t-1}\tilde{X}_{t-1}$. This study also constructs $\hat{\Omega}_{x,t}$ and $\hat{\Sigma}_{v,t}$ using the kernel density:

$$\hat{\Omega}_{x,t} = T^{-1}\sum_{s=1}^{T} K_b\bigg(\frac{s-t}{T}\bigg)\tilde{X}_{s-1}\tilde{X}'_{s-1},\ \hat{\Sigma}_{v,t} = T^{-1}\sum_{s=1}^{T} K_b\bigg(\frac{s-t}{T}\bigg)\hat{v}_s\hat{v}'_s \tag{D.8}$$

where $b = b_c$ is the average bandwidth across the K equations, which is used by Adrian et al. (2015).

2. Let $A_{i,t} = (\hat{A}_{0,i,t-1}, \hat{A}'_{1,i,t-1}, \hat{\beta}'_{i,t-1})$ and $\hat{A}_{i,t}$ is estimated by equation (D.2) using the short-run bandwidth. Then, $\hat{\Omega}_{f,t}$ and $\hat{\Sigma}_{e,t}$ are obtained by the kernel

estimation as:

$$\hat{\Omega}_{F,t} = T^{-1}\sum_{s=1}^{T} K_b\left(\frac{s-t}{T}\right)\tilde{F}_{s-1}\tilde{F}'_{s-1},\ \hat{\Sigma}_{e,t} = T^{-1}\sum_{s=1}^{T} K_b\left(\frac{s-t}{T}\right)\hat{e}_s\hat{e}'_s \qquad \text{(D.9)}$$

where $\hat{e}_i = R_{i,t} - \hat{A}_{i,t-1}z_t^{tv}$ and $b = b_c$ is the average bandwidth that is used by Adrian et al. (2015).

3. The risk price parameters $\hat{\Lambda}^{tv}$ are estimated by equation (5.9). The variance estimators $\hat{v}_{\Lambda,1}^{tv}$ and $\hat{v}_{\Lambda,2}^{tv}$ are constructed as:

$$\begin{aligned}
\hat{v}_{\Lambda,1} = \quad & T \quad \left[\sum_{t=1}^{T}(\hat{\Omega}_{f,t}\otimes\hat{B}'_{t-1}\hat{B}_{t-1})\right]^{-1} \\
\times \quad & \left[\sum_{t=1}^{T}((\hat{\Omega}_{f,t}\hat{\Lambda}^{tv}D'_B\hat{\Omega}_{z,t}^{-1}D_B\hat{\Lambda}^{tv}\hat{\Omega}_{f,t}+\hat{\Omega}_{f,t})\otimes\hat{B}'_{t-1}\hat{\Sigma}_{e,t}\hat{B}_{t-1})\right] \\
\times \quad & \left[\sum_{t=1}^{T}(\hat{\Omega}_{f,t}\otimes\hat{B}'_{t-1}\hat{B}_{t-1})\right]^{-1} \qquad \text{(D.10)}
\end{aligned}$$

where

$$\hat{\Omega}_{z,t} = T^{-1}\sum_{s=1}^{T} K_b\left(\frac{s-t}{T}\right)z_s^{tv}z_s^{tv\prime}, \qquad \text{(D.11)}$$

$$D_B = (A_t)^{-1}B_t, \qquad \text{(D.12)}$$

and

$$\begin{aligned}
\hat{v}_{\Lambda,2} = \quad & T \quad \left[\sum_{t=1}^{T}(\hat{\Omega}_{f,t}\otimes\hat{B}'_{t-1}\hat{B}_{t-1})\right]^{-1} \\
\times \quad & \left[\sum_{t=1}^{T}(\hat{\Omega}_{f,t}\otimes\hat{B}'_{t-1}\hat{B}_{t-1}\hat{\Sigma}_{u,t}\hat{B}'_{t-1}\hat{B}_{t-1})\right] \\
\times \quad & \left[\sum_{t=1}^{T}(\hat{\Omega}_{f,t}\otimes\hat{B}'_{t-1}\hat{B}_{t-1})\right]^{-1}. \qquad \text{(D.13)}
\end{aligned}$$

Finally, $\hat{v}_{\Lambda} = \hat{v}_{\Lambda,1} + \hat{v}_{\Lambda,2}$ is obtained and this heteroskedasticity robust variance estimator is used for the risk price parameters of the time-varying beta and risk price model.

D.2 Global Bid-ask Spreads

This study uses the global bid-ask spreads as a forecast factor to capture FX market liquidity, instead of the TED spread. $BAS_{FX,t}$ is the global bid-ask spreads as in Menkhoff et al. (2012a). A similar approach is used to $VOL_{FX,t}$ and the global FX bid-ask spread measure, $\psi_{FX,t}$, in month t is obtained as:

$$\psi_{FX,t} = \frac{1}{T_t} \sum_{\tau=1}^{T_t} \sum_{j=1}^{K_\tau} \left(\frac{\psi_{j,\tau}}{K_\tau} \right) \tag{D.14}$$

where $\psi_{j,\tau}$ is the bid ask spread measure of spot exchange rate j at day τ.

TABLE D.1: Risk Price Parameter Estimates: Constant Beta Model

Panel A: All countries

	Risk Factor	λ_0	Forecast Factors VOL_{FX}	CRB	TED	$\bar{\lambda}$
(a)	DOL	0.77**	-1.41			0.18
		(0.38)	(0.87)			(0.12)
	HML_{FX}	2.20***	-4.11***			0.49***
		(0.37)	(0.85)			(0.13)
(b)	DOL	0.17		0.10*		0.18
		(0.12)		(0.04)		(0.13)
	HML_{FX}	0.46***		0.15***		0.49***
		(0.12)		(0.04)		(0.13)
(c)	DOL	0.59***			-0.78***	0.18
		(0.19)			(0.29)	(0.14)
	HML_{FX}	0.99***			-0.98***	0.49***
		(0.29)			(0.28)	(0.14)

Panel B: Developed countries

	Risk Factor	λ_0	Forecast Factors VOL_{FX}	CRB	TED	$\bar{\lambda}$
(d)	DOL	0.59	-0.85			0.19
		(0.45)	(0.91)			(0.14)
	HML_{FX}	1.95***	-3.42***			0.34**
		(0.45)	(0.90)			(0.15)
(e)	DOL	0.17		0.11**		0.19
		(0.13)		(0.05)		(0.14)
	HML_{FX}	0.32**		0.11**		0.34**
		(0.14)		(0.05)		(0.15)
(f)	DOL	0.64***			-0.87***	0.19
		(0.21)			(0.32)	(0.16)
	HML_{FX}	0.94***			-1.15***	0.34***
		(0.32)			(0.32)	(0.16)

Notes: This table presents risk price parameters estimated by the constant beta and time-varying risk price model as in Adrian et al. (2015). The test assets of Panel A are six forward discount sorted all country currency portfolios and those of Panel B are five forward discount sorted developed country currency portfolios. The risk price parameters are obtained by equation (5.5) and the average risk price $\bar{\lambda}$ is obtained by equation (5.6). The risk factors are the dollar (DOL) and the return spread between high and low interest rate currency portfolios (HML_{FX}) as in Lustig et al. (2011). The forecast factors are global FX volatility (VOL_{FX}) as in Menkhoff et al. (2012a), CRB Raw industrial material subindex return (CRB) as in Bakshi and Panayotov (2013), and TED spread (TED). Heteroskedasticity robust standard errors are reported in parentheses. Asterisk *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

TABLE D.2: Risk Price Parameter Estimates: Time-varying Beta Model

Panel A: All countries

	Risk Factor	λ_0	Forecast Factors VOL_{FX}	CRB	TED	$\bar{\lambda}$
(a)	DOL	0.85**	-1.49*			0.22
		(0.36)	(0.81)			(0.12)
	HML_{FX}	2.07***	-3.81***			0.48***
		(0.36)	(0.82)			(0.12)
(b)	DOL	0.19*		0.11***		0.21*
		(0.11)		(0.04)		(0.11)
	HML_{FX}	0.43***		0.12***		0.45***
		(0.12)		(0.04)		(0.12)
(c)	DOL	0.63***			-0.78***	0.23**
		(0.17)			(0.26)	(0.11)
	HML_{FX}	0.86***			-0.86***	0.41***
		(0.18)			(0.26)	(0.11)

Panel B: Developed countries

	Risk Factor	λ_0	Forecast Factors VOL_{FX}	CRB	TED	$\bar{\lambda}$
(d)	DOL	0.52	-0.75			0.17
		(0.43)	(0.85)			(0.13)
	HML_{FX}	1.83***	-3.25***			0.30**
		(0.41)	(0.83)			(0.13)
(e)	DOL	0.20		0.12***		0.22*
		(0.13)		(0.04)		(0.13)
	HML_{FX}	0.29**		0.08*		0.30**
		(0.13)		(0.04)		(0.13)
(f)	DOL	0.71***			-0.88***	0.25**
		(0.20)			(0.29)	(0.12)
	HML_{FX}	0.85***			-1.02***	0.31**
		(0.23)			(0.34)	(0.14)

Notes: This table presents risk price parameters estimated by the time-varying beta and risk price model as in Adrian et al. (2015). The test assets of Panel A are six forward discount sorted all country currency portfolios and those of Panel B are five forward discount sorted developed country currency portfolios. The risk price parameters are obtained by equation (5.10) and the average risk price $\bar{\lambda}$ is obtained by equation (5.11). The risk factors are the dollar (DOL) and the return spread between high and low interest rate currency portfolios (HML_{FX}) as in Lustig et al. (2011). The forecast factors are global FX volatility (VOL_{FX}) as in Menkhoff et al. (2012a), CRB Raw industrial material subindex return (CRB) as in Bakshi and Panayotov (2013), and TED spread (TED). Heteroskedasticity robust standard errors are reported in parentheses. Asterisk *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

TABLE D.3: Risk Price Parameter Estimates: Constant Beta Model and Global Bid-ask Spreads

Panel A: All countries

	Risk Factor	λ_0	Forecast Factors VOL_{FX}	CRB	BAS_{FX}	$\bar{\lambda}$
(a)	DOL_{FX}	0.35			-1.46	0.18
		(0.37)			(3.10)	(0.12)
	HML_{FX}	1.39***			-8.08***	0.49***
		(0.36)			(3.03)	(0.13)
(b)	DOL_{FX}	0.43	-1.05	0.09*	1.58	0.18
		(0.44)	(1.06)	(0.04)	(3.59)	(0.13)
	HML_{FX}	1.95***	-3.34***	0.10**	-0.73	0.49***
		(0.42)	(1.02)	(0.04)	(3.41)	(0.14)

Panel B: Developed countries

	Risk Factor	λ_0	Forecast Factors VOL_{FX}	CRB	BAS_{FX}	$\bar{\lambda}$
(c)	DOL_{FX}	0.03			2.15	0.19
		(0.37)			(4.56)	(0.16)
	HML_{FX}	0.74**			-5.35	0.34**
		(0.38)			(4.64)	(0.15)
(d)	DOL_{FX}	0.08	-0.25	0.11**	2.79	0.19
		(0.60)	(0.93)	(0.05)	(4.55)	(0.15)
	HML_{FX}	2.28***	-3.18***	0.06	-6.03	0.34**
		(0.60)	(0.94)	(0.05)	(4.56)	(0.17)

Notes: This table presents risk price parameters estimated by the constant beta and time-varying risk price model as in Adrian et al. (2015). The test assets of Panel A are six forward discount sorted all country currency portfolios and those of Panel B are five forward discount sorted developed country currency portfolios. The risk price parameters are obtained by equation (5.5) and the average risk price $\bar{\lambda}$ is obtained by equation (5.6). The risk factors are the dollar (DOL) and the return spread between high and low interest rate currency portfolios (HML_{FX}) as in Lustig et al. (2011). The forecast factors are global FX volatility (VOL_{FX}) as in Menkhoff et al. (2012a), CRB Raw industrial material subindex return (CRB) as in Bakshi and Panayotov (2013), and BAS_{FX} is the global bid-ask spreads as in Menkhoff et al. (2012a). Wald indicates the Heteroskedasticity robust standard errors are reported in parentheses. Asterisk *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

TABLE D.4: Risk Price Parameter Estimates: Time-varying Beta Model and Global Bid-ask Spreads

Panel A: All countries

			Forecast Factors			
	Risk Factor	λ_0	VOL_{FX}	CRB	BAS_{FX}	$\bar{\lambda}$
(a)	DOL	0.40			-1.69	0.21*
		(0.36)			(2.98)	(0.12)
	HML_{FX}	1.22***			-6.21**	0.53***
		(0.35)			(2.90)	(0.11)
(b)	DOL	0.46	-1.24	0.09**	2.61	0.25**
		(0.43)	(0.98)	(0.04)	(3.49)	(0.12)
	HML_{FX}	2.01***	-3.31***	0.07*	-1.69	0.46***
		(0.42)	(0.96)	(0.04)	(3.41)	(0.14)

Panel B: Developed countries

			Forecast Factors			
	Risk Factor	λ_0	VOL_{FX}	CRB	BAS_{FX}	$\bar{\lambda}$
(c)	DOL	0.08			1.37	0.18
		(0.34)			(4.16)	(0.13)
	HML_{FX}	0.71*			-5.08	0.33**
		(0.36)			(4.43)	(0.15)
(d)	DOL	0.14	-0.22	0.10**	2.24	0.22*
		(0.51)	(0.79)	(0.04)	(3.81)	(0.11)
	HML_{FX}	2.19***	-3.28***	0.05	-4.63	0.30**
		(0.61)	(0.95)	(0.05)	(4.55)	(0.14)

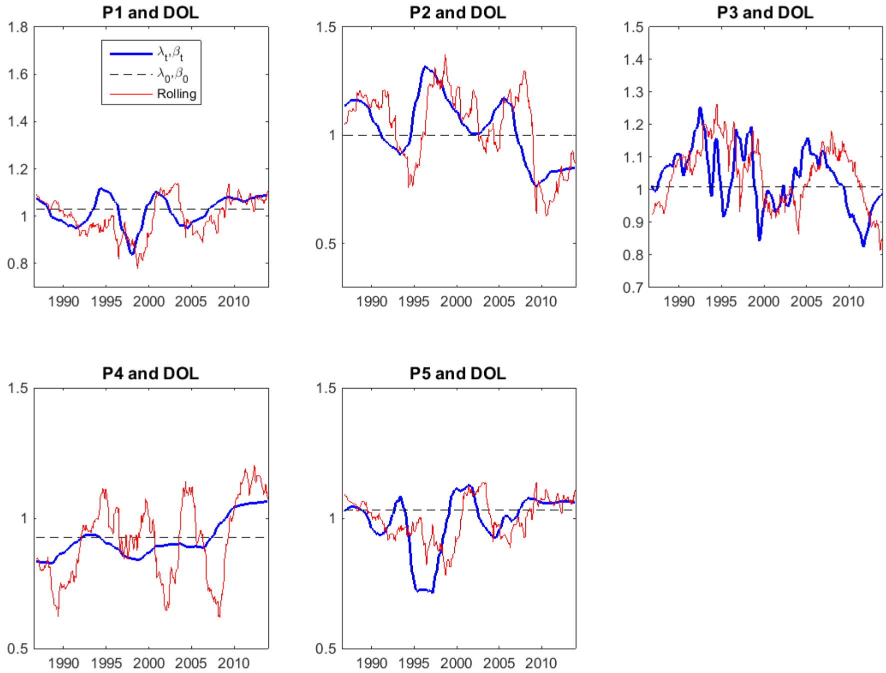
Notes: This table presents risk price parameters estimated by the time-varying beta and risk price model as in Adrian et al. (2015). The test assets of Panel A are six forward discount sorted all country currency portfolios and those of Panel B are five forward discount sorted developed country currency portfolios. The risk price parameters are obtained by equation (5.10) and the average risk price $\bar{\lambda}$ is obtained by equation (5.11). The risk factors are the dollar (DOL_{FX}) and the return spread between high and low interest rate currency portfolios (HML_{FX}) as in Lustig et al. (2011). The forecast factors are global FX volatility (VOL_{FX}) as in Menkhoff et al. (2012a), CRB Raw industrial material subindex return (CRB) as in Bakshi and Panayotov (2013), and BAS_{FX} is the global bid-ask spreads as in Menkhoff et al. (2012a). Heteroskedasticity robust standard errors are reported in parentheses. Asterisk *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

TABLE D.5: Risk Price Parameters Estimates excluding the Crisis

	Risk Factor	λ_0	Forecast Factors VOL_{FX}	CRB	TED	$\bar{\lambda}$
Constant beta and time-varying risk price model						
Panel A: All countries						
(a)	DOL	0.12	0.51	0.00	-0.19	0.23
		(0.49)	(1.10)	(0.06)	(0.37)	(0.13)
	HML_{FX}	2.04***	-2.89***	0.07	-0.62	0.55***
		(0.50)	(1.12)	(0.06)	(0.37)	(0.15)
Panel B: Developed countries						
(b)	DOL	-0.14	1.09	-0.01	-0.20	0.23
		(0.62)	(0.86)	(0.06)	(0.40)	(0.15)
	HML_{FX}	1.81***	-2.16*	0.01	-0.71*	0.46***
		(0.62)	(1.26)	(0.06)	(0.39)	(0.15)
Time-varying beta and time-varying risk price model						
Panel C: All countries and time-varying beta model						
(c)	DOL	0.19	0.39	-0.01	-0.11	0.28**
		(0.44)	(1.00)	(0.05)	(0.34)	(0.12)
	HML_{FX}	1.97***	-2.85***	0.06	-0.60	0.50***
		(0.48)	(1.08)	(0.06)	(0.37)	(0.13)
Panel D: Developed countries						
(d)	DOL	-0.16	1.18	-0.04	-0.18	0.25*
		(0.62)	(1.25)	(0.06)	(0.39)	(0.14)
	HML_{FX}	1.89	-3.81	-0.10	0.03	0.18
		(3.28)	(6.62)	(0.33)	(2.07)	(0.74)

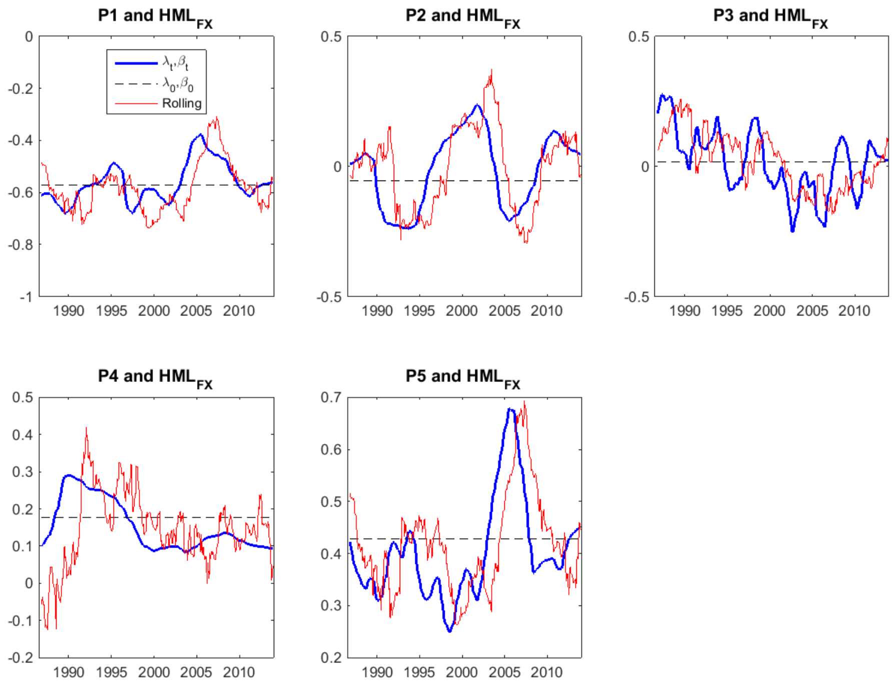
Notes: This table presents risk price parameters estimated by the constant beta and time-varying risk price model and the time-varying beta and risk price model as in Adrian et al. (2015). Data extend to November 1983 to March 2008 to exclude the effect of the global financial crisis. The test assets of Panels A and C are six forward discount sorted all country currency portfolios and those of Panels B and D are five forward discount sorted developed country currency portfolios. The risk price parameters in Panels A and B are obtained by equation (5.5) and the average risk price $\bar{\lambda}$ in Panels A and C are obtained by equation (5.6). The risk price parameters in Panels C and D are obtained by equation (5.10) and the average risk price $\bar{\lambda}$ in Panels C and D is obtained by equation (5.11). The risk factors are the dollar (DOL) and the return spread between high and low interest rate currency portfolios (HML_{FX}) as in Lustig et al. (2011). The forecast factors are global FX volatility (VOL_{FX}) as in Menkhoff et al. (2012a), CRB Raw industrial material subindex return (CRB) as in Bakshi and Panayotov (2013), and TED spread (TED). Heteroskedasticity robust standard errors are reported in parentheses. Asterisk *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

FIGURE D.1: Comparison of time series portfolio betas on DOL in developed countries



This figure provides plots of the estimated time series of betas on the dollar (DOL) in developed countries. λ_t, β_t denotes the time-varying beta and risk price model and the betas are obtained by equation (5.9) (thick blue line). λ_t, β_0 denotes the constant beta and time-varying risk price model and the betas are obtained by equation (5.3) (dashed black line). Rolling denotes the 36 months rolling window beta (thin red line). The time-varying betas are estimated by the kernel regression approach as in Adrian et al. (2015).

FIGURE D.2: Comparison of time series portfolio betas on HML_{FX} in developed countries

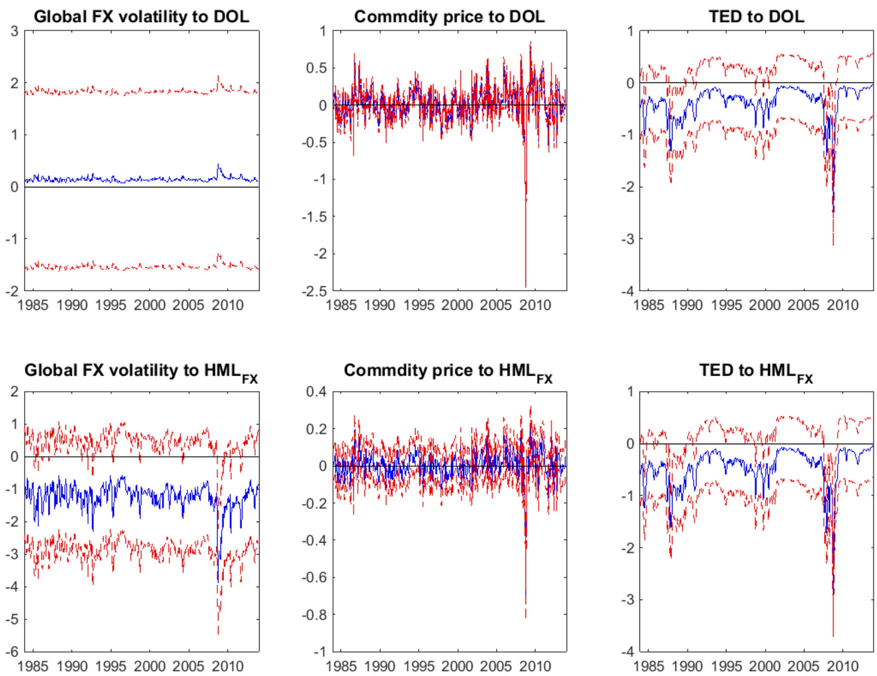


Notes: This figure provides plots of the estimated time series of betas on the return spread between high and low interest rate currency portfolios (HML_{FX}) in developed countries. λ_t, β_t denotes the time-varying beta and risk price model and the betas are obtained by equation (5.9) (thick blue line). λ_t, β_0 denotes the constant beta and time-varying risk price model and the betas are obtained by equation (5.3) (dashed red line). Rolling denotes the 36 months rolling window beta (thin black line).

FIGURE D.3: Time-varying risk prices (λ) of DOL in HML_{FX} in developed countries

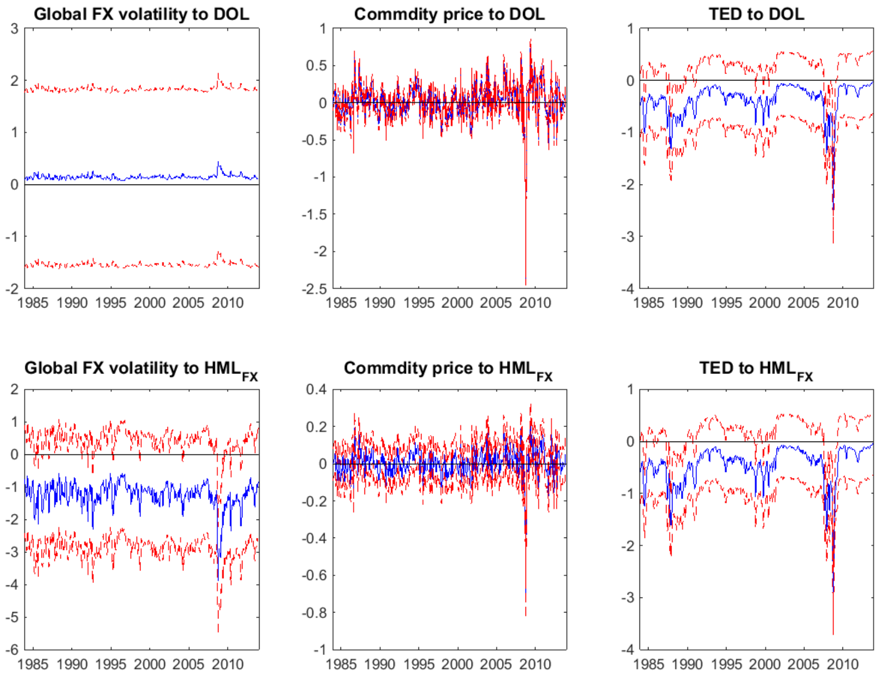
Notes: This figure displays time series risk prices of the dollar (DOL) and the return spread between high and low interest rate currency portfolios (HML_{FX}) with their 95% confidence intervals in developed countries. The risk prices are obtained as $\lambda = \lambda_0 + \Lambda_1 F_t$. Three forecast factors are global FX volatility (VOL_{FX}) as in Menkhoff et al. (2012a), CRB Raw industrial material subindex return (CRB) as in Bakshi and Panayotov (2013), and TED spread (TED).

FIGURE D.4: Contribution of forecast factors in developed countries



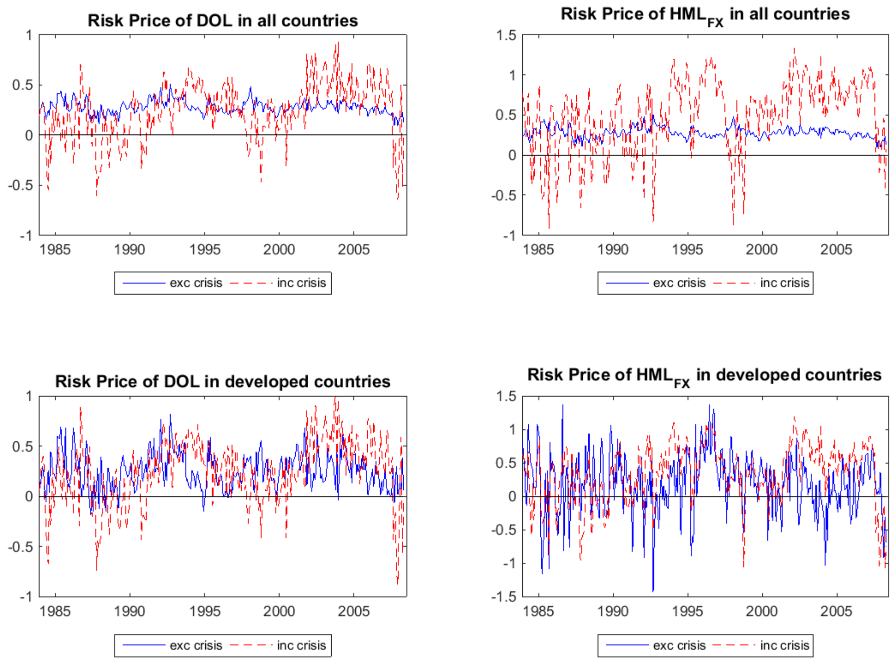
Notes: This figure displays the contribution of the three forecast factors with their 95% confidence intervals in developed countries. The contribution is estimated as $\Lambda_{1,j}F_{j,t}$. The forecast factors are global FX volatility (VOL_{FX}) as in Menkhoff et al. (2012a), CRB Raw industrial material subindex return (CRB) as in Bakshi and Panayotov (2013), and TED spread (TED).

FIGURE D.5: Time-varying risk price (λ) of ΔVOL_{FX}



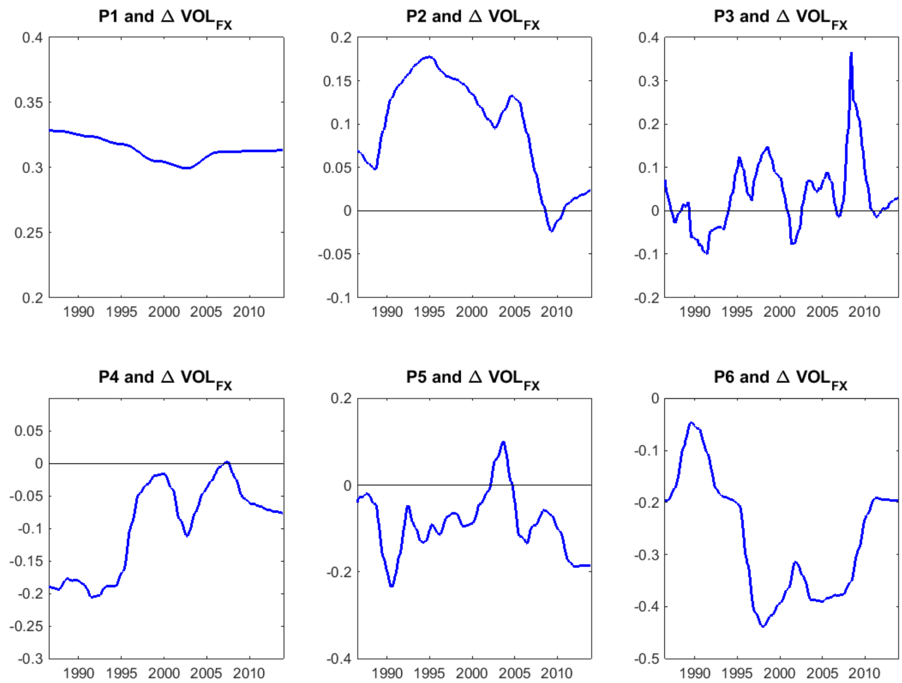
Notes: This figure displays time series risk price of the global FX volatility innovations (ΔVOL_{FX}) with its 95% confidence interval. Risk price parameters are obtained by the time-varying beta and risk price model. The risk prices are obtained as $\lambda = \lambda_0 + \Lambda_1 F_t$. The test assets of the upper figure are six forward discount sorted all country currency portfolios and those of the lower figure are five forward discount sorted developed country currency portfolios. The forecast factors are global FX volatility (VOL_{FX}) as in Menkhoff et al. (2012a), CRB Raw industrial material subindex return (CRB) as in Bakshi and Panayotov (2013), and TED spread (TED).

FIGURE D.6: Time-varying risk price comparison



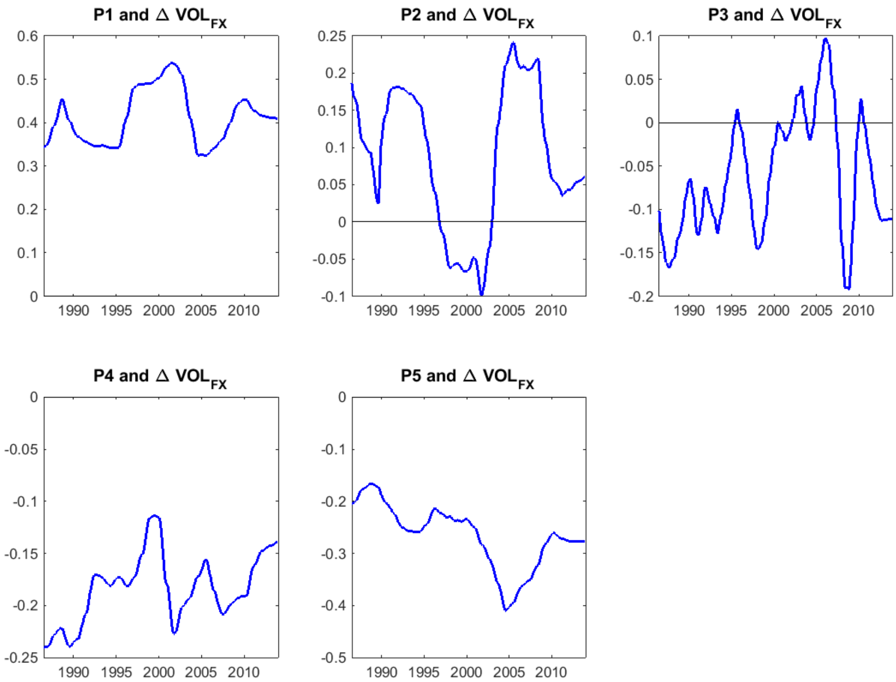
Notes: This figure displays time series risk price of the dollar risk (DOL) and the return spread between high and low interest rate currency portfolios (HML_{FX}). Risk price parameters are obtained by the time-varying beta and risk price model. exc crisis denotes the estimation results using data which cover November 1983 to March 2008. inc crisis denotes the estimation results using data which cover November 1983 to December 2013. The forecast factors are global FX volatility (VOL_{FX}) as in Menkhoff et al. (2012a), CRB Raw industrial material subindex return (CRB) as in Bakshi and Panayotov (2013), and TED spread (TED).

FIGURE D.7: Time-varying betas on ΔVOL_{FX}



Notes: This figure provides plots of the estimated time series of betas on ΔVOL_{FX} which is the global FX volatility innovation factor as in Menkhoff et al. (2012a). The time-varying betas are obtained by equation (5.9). The test assets are six forward discount sorted all country currency portfolios.

FIGURE D.8: Time-varying betas on ΔVOL_{FX} in developed countries



Notes: This figure provides plots of the estimated time series of betas on ΔVOL_{FX} which is the global FX volatility innovation factor as in Menkhoff et al. (2012a). The time-varying betas are obtained by equation (5.9). The test assets are six forward discount sorted all country currency portfolios.

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